Curb your enthusiasm: the aggregate short-run effects of a borrower-based measure

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Abstract
We estimate the ex-post short-run (6 months) impact of the Portuguese macroprudential borrower-based measure on new loans for house purchase and consumption, on house prices and on the economic activity. The macroprudential measure introduced a set of recommendations on the criteria used by banks in borrowers' creditworthiness assessment: i) limits to LTV and DSTI ratios and to maturity and ii) the requirement of regular payments of interest and principal. In an ideal scenario, the impact of this set of restrictions would be measured by comparing the path of the variables after the introduction of the measure to their path in a no-policy change scenario, usually called the counterfactual. However, the no-policy change scenario is not observable and, therefore, needs to be estimated under some assumptions. We use a Bayesian VAR model to estimate the counterfactual of the variables of interest in the 6 months after the introduction of the policy. Our analysis suggests that the measure contributed to curb the growth of new loans granted to households, both for house purchase and consumption, 4 months after its implementation. We do not find evidence that the macroprudential measure had a significant impact on house prices or on economic activity, in the 6 months following its introduction. (JEL: C54, E44, E47, E58)

1. Introduction

In February 2018, the Banco de Portugal announced the implementation of a borrower-based macroprudential measure, which entered into force in July 2018 as a recommendation (hereinafter referred to as Recommendation or policy) under a regime of comply or explain. The Recommendation applies to new loans granted to households for house purchase and consumption and introduces a set of limits to i) loan-to-value (LTV) ratio, ii) debt-service-to-income (DSTI) ratio and iii) maturity and the requirement of regular payment of interests and principal. The limit imposed to the DSTI ratio is applicable to a ratio that comprises both interest rate and income shocks and considers the overall amount of payments associated with household debt (including loans for house purchase and consumption). The simultaneous introduction of limits to the LTV ratio, to the DSTI ratio and to the maturity overcomes the shortcomings

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associated to the implementation of each individual instrument per se and reinforces the effectiveness of the Recommendation as discussed in Leal and Lima (2018).

The objective of the Recommendation is twofold: i) enhance financial sector resilience against adverse shocks by preventing excessive risk taking when granting credit; and ii) minimize the default risk of households by promoting access to sustainable financing. Overall, it is designed to prevent the build-up of systemic risk and was calibrated to have an impact on lending to borrowers with a high risk profile (high LTV and/or high DSTI ratios), i.e. borrowers that in a downturn are more likely to default and/or if in default will imply a higher loss for the bank, thus putting pressure on banks profitability. The Recommendation does not aim to affect the general lending activity to households or the dynamics of house prices, although it may have a mitigating effect on the feedback loop between both variables. Some flexibility was considered in the design of the Recommendation also to prevent a disrupting impact on credit activity. In particular, part of new credit agreements, such as credit cards, were excluded from its scope of application.[1]

The timing of the introduction of the Recommendation reflected the emergence of signs of some relaxation in credit standards by banks in Portugal. Moreover, the steady increase of new lending to households in a context of low interest rates and a recovering economic environment was creating incentives for higher competition among banks and a further relaxation of credit standards. This context, in tandem with the high level of household indebtedness and low savings rate, could pose a threat to future financial stability, notably in the case of an increase of interest rates or a deterioration of economic conditions.

This analysis aims at assessing the impact of the Recommendation just described in the 6 months following its implementation on a set of financial and macroeconomic variables. In particular, we are especially interested in the impact of the Recommendation on the level of new loans for house purchase and for consumption. Additionally, we examine its potential impact on the dynamics of house prices and economic activity.

To disentangle the effects of the Recommendation we conduct a counterfactual analysis, i.e. a characterization of the evolution of new loans granted to households, both for consumption and house purchase purposes, house prices and economic activity in a no-policy change scenario, and compare it with the observed post-Recommendation data.

The specification of a counterfactual scenario to study the policy impact on aggregate variables is a common approach in the literature. This framework has been used to assess the impact of measures from different policy areas and hence, can also be applied to assess the impact of macroprudential measures. Both Bloor and McDonald (2013) and Cussen *et al.* (2015) use a Bayesian Vector Autoregression (BVAR) model to provide an ex-ante estimate of the impact of introducing a LTV ratio limit in New Zealand and

1. For detailed information on the limits set by the Recommendation upon its announcement that remained applicable during the period considered in this article see `https://www.bportugal.pt/sites/default/files/macroprudential_measure_background_doc.pdf`.

in Ireland, respectively. Their approach is to impose a shock to the BVAR model that mimics the introduction of the measure in order to compute the counterfactual scenario. Bloor and McDonald (2013) specify this shock as a reduction of house sales or as an increase in mortgage interest rates. In contrast, Cussen *et al.* (2015) define the shock as a reduction in new loans for house purchase, which is estimated by simulating the impact of the introduction of the policy measure using loan-level data.

Both ex-ante studies estimate a negative impact of the LTV ratio restriction on housing credit growth and on house prices. In particular, Cussen *et al.* (2015) find that the effect on house prices is reduced in the initial months and peaks in the third year after the policy measure's introduction.

Price (2014) evaluates the ex-post impact of the introduction of a LTV ratio in New Zealand by estimating a counterfactual using forecasts for the relevant variables based on a BVAR model. Results suggest that the LTV ratio restriction reduced the number of house transactions and mortgages approvals in the first 6 months of implementation, while it had no statistically significant effect on credit growth nor on house prices.[2]

Following Price (2014), we specify a BVAR model which accounts for the historical relationships between new loans for house purchase, new loans for consumption, house prices and economic activity before the introduction of the Recommendation. The model is estimated using information prior to the policy implementation and the counterfactual values for the variables of interest correspond to the forecasts of the model in the 6 months following the policy intervention. The difference between the observed values of the variables of interest and their counterfactual values reflects the potential impact of the macroprudential policy measure.

The results suggests that the Recommendation contributed to curb the volume of new loans granted to households, both for house purchase and consumption, 4 months after the introduction of the policy. Under our estimated counterfactual, house prices would continue to grow at a similar rate as before the implementation of the Recommendation. However, observed house prices are higher than the counterfactual and this difference is statistically significant after 4 months. It is nevertheless unlikely that this difference is caused by the Recommendation as tighter credit standards are expected to either have no effect or a negative impact on house prices (Ahuja and Nabar 2011; Igan and Kang 2011). The difference between the observed house prices and the estimated counterfactual values might be explained by the historically unprecedented buoyancy in the Portuguese housing market since 2017. House prices have shown signs of overvaluation since the beginning of 2018 (Banco de Portugal 2019b). The recent increase of residential investment by non-residents, that do not borrow from the domestic credit market and, therefore, are not affected by the Recommendation, was an important factor that contributed to the buoyancy of the Portuguese housing market. In fact, as documented in Banco de Portugal (2019b), residential investment by non-residents during 2018 increased in relation to investment

2. An alternative approach considered in the literature on the impact of macroprudential policy is to estimate a counterfactual scenario using DSGE models. For a broad overview of both theoretical and empirical contributions to the literature on macroprudential policy see Galati and Moessner (2018).

by residents, while the percentage of transactions financed with domestic bank credit remained constant. Finally, we do not find evidence of a statistically significant effect of the Recommendation on economic activity in the 6 months following its introduction.

2. Methodology, variables and data used

2.1. Methodology

In order to develop a counterfactual scenario, we specify a VAR model, and estimate it using Bayesian techniques. Let $y_t = (y_{1t}, y_{2t}, ..., y_{nt})'$ be a $(n \times 1)$ vector of endogenous variables to be forecasted and $x_t = (x_{1t}, x_{2t}, ..., x_{mt})'$ a $(m \times 1)$ vector of control variables. Under a VAR(p) model, each one of the time series to be forecasted is assumed to be a linear function of their past values, of the past values of the remaining variables included in y_t up to p lags and of the control variables such that

$$y_t = A_1 y_{t-1} + ... + A_p y_{t-p} + C x_t + E_t \ , \tag{1}$$

where $t = 1, ..., T$, A_j, $j = 1, ..., p$, are $(n \times n)$ matrices of autoregressive coefficients, C is an $(n \times m)$ matrix of coefficients associated with the set of control variables and E_t=$(E_{1t}, E_{2t}, ..., E_{nt})'$ is an $(n \times 1)$ vector of innovations that follow a multivariate normal distribution $E \sim N(0, \Sigma)$. The estimation of the model considers data on a monthly frequency and the sample runs from 2003M3 to 2018M6. The BIC criteria is used to select the lag order of the BVAR model.

The endogenous variables (variables of interest) considered are (i) new loans granted to households for consumption (ii) new loans granted to households for house purchase, (iii) the real house prices index, to account for interdependences with credit dynamics, and (iv) a proxy for the economic activity. A rise in house prices can reinforce credit growth as the value of the property, which is usually pledged as collateral, increases. At the same time, credit growth can contribute to a further increase in house prices. Therefore, there is a feedback loop effect between the two variables that must be taken into account, fitting in with the VAR framework.

Because both credit and housing markets are influenced by external factors, we let the forecasts be influenced by the observed path of a set of control variables. Considering that the control variables are included in the model contemporaneously, we use their realized values when computing the forecasts. In order to properly estimate the counterfactual, this set of controls only includes variables that are not supposed to be affected (at least in the short-run) by the Recommendation. The selection of the control variables was based on the results of studies that delve into the main determinants of credit granted to households in Portugal, such as Castro and Santos (2010), and of housing market developments such as Lourenço and Rodrigues (2017). The variables selected as controls are i) residential investment by residents (gross fixed capital formation), ii) residential investment by non-residents (foreign direct investment in housing which includes house purchases by non-residents), iii) the 12-month Euribor rate, to account for bank funding costs, and iv) the year-on-year rate of change of the euro area GDP to account for external economic environment.

The estimation of VAR models using Bayesian techniques has become an increasingly popular approach in forecasting settings. VAR models typically include a large number of parameters, thus raising the risk of overfitting the data and, consequently, of undermining the forecasting accuracy of the model. This risk increases when the model is estimated with relatively short times series. BVAR models, in turn, rely on the ability of Bayesian techniques to shrink the estimates towards a predefined set of prior beliefs about the distribution of the parameters, which ultimately leads to a reduction in the variance of the parameter estimates and to an improvement in forecast performance; see Karlsson (2013).

To specify the prior distribution of the VAR(p) parameters we adopt the Minnesota (or Litterman) prior (Doan *et al.* 1984). The main idea behind this prior is to shrink the slope estimates towards a multivariate random walk model. In addition to its simplicity, this approach has been found useful to predict economic time series.[3]

After estimating the model, the counterfactual for each variable of interest is obtained as the median of the posterior predictive distribution of the endogenous variable, that is, the distribution of future realizations of the endogenous variable over the h horizon, conditional on the information set, using the algorithm proposed by Karlsson (2013). The calculations were made in MATLAB employing the Bayesian Estimation, Analysis and Regression (BEAR) Toolbox; see Dieppe *et al.* (2016) for details.

2.2. Data

2.2.1. Endogenous variables

Credit variables are compiled by Banco de Portugal. We use new loans, instead of stocks, as this variable is expected to react quicker to the implementation of the Recommendation. We have also disaggregated new loans for house purchase from new loans for consumption as the policy measure encompasses both types of loans and may have a differentiated effect on each of them. To reduce the noise in the monthly flows of new lending time series, which could blur the results, we considered the quarterly flows of new loans.

The real house price index, deflated using HICP, was obtained from the OECD database on house prices (original source INE). This index is published on a quarterly frequency, and we have used linear interpolation to obtain a monthly index.

The proxy for developments in economic activity is the coincident indicator published by Banco de Portugal. This indicator, described in Rua (2004), summarizes the information of a set of indicators that are useful to monitor the evolution of economic activity and closely tracks the rate of change of gross domestic product (GDP). The main

3. In appendix A, we detail the specification and estimation of the BVAR, as well as the approach for the calibration of the hyperparameters governing the prior distribution.

advantage of using this synthetic indicator instead of the rate of change of GDP is that it is available at a monthly frequency, thus avoiding the need for interpolation.

2.2.2. *Control variables*

Residential investment by residents is published by OECD (original source INE) and residential investment by non-residents is published by Banco de Portugal. As these variables are both published on quarterly basis, we interpolate them using a linear rule as we did for house prices.

The 12-month Euribor rate is published by the ECB. We use the monthly time series, which is computed as the average of observations through the period. This variable aims to control for bank funding costs as it is the most common reference interest rate applied to new loans for house purchase in 2017 and 2018 in Portugal[4], which, in turn, accounts for the larger share of loans granted to households.

The year-on-year rate of change of the euro area GDP, used to control for the international macroeconomic environment given that Portugal is a small open economy, is published by the ECB. A linear interpolation is applied to obtain the series in monthly frequency.

Variables enter the model in log levels if not expressed as a rate or index. Table 1 summarizes the transformations applied to the variables, the type of variables and the data sources.

Variable	Transformations	Type	Source
New loans for consumption	s.a., quarterly flows, log	Endogenous	Banco de Portugal
New loans for house purchase	s.a., quarterly flows, log	Endogenous	Banco de Portugal
Real house price index	s.a., interpolation	Endogenous	INE, OECD
Coincident indicator	-	Endogenous	Banco de Portugal
Residential Investment by residents	s.a., interpolation, log	Control	INE, OECD
12-month Euribor	-	Control	ECB
Residential investment by non-residents	interpolation, log	Control	Banco de Portugal
Euro area GDP	s.a., interpolation, yoy rate of change	Control	Banco de Portugal

TABLE 1. Variables and transformations

Notes: Interpolation from quarterly to monthly frequency is achieved using a linear rule. S.a. stands for seasonal adjusted. Seasonal adjustment of new loans for consumption and house purchase is performed using the automatic procedures of X-13ARIMA-SEATS, the remaining variables are published with the seasonal adjustment.

4. According to Banco de Portugal (2018) the percentage of new loans for house purchase indexed to the 12-month Euribor was 94.4% in 2018 and 92.8% in 2017. The variable interest rate regime is the most predominant in new loans for house purchase in Portugal, accounting for 87.8% and 83.2% of the total amount granted in 2018 and 2017, respectively.

2.3. *Data analysis*

We begin by examining the evolution of the endogenous variables[5] (Figure 1), before and after the policy implementation. In the period leading to 2008, new loans to households were at historical highs. House transactions were mainly funded through new loans for house purchase and residential investment was largely made by residents. The global financial crisis then triggered a severe contraction of the global economy, which was then reinforced during the euro area sovereign debt crisis, having a significant negative impact on the Portuguese economic activity. This led to a decrease in disposable income and, consequently, to a decrease in consumption and residential investment. Additionally, and as a consequence of a tightening of credit standards, new lending to households, during this latter period, recorded a major contraction, more pronounced for new loans for house purchase that remained on very low levels until 2014. During this period, house prices also recorded a significant reduction, although not as severe as in other euro area countries where, in contrast to Portugal, there was evidence of house price overvaluation leading up to the crisis.

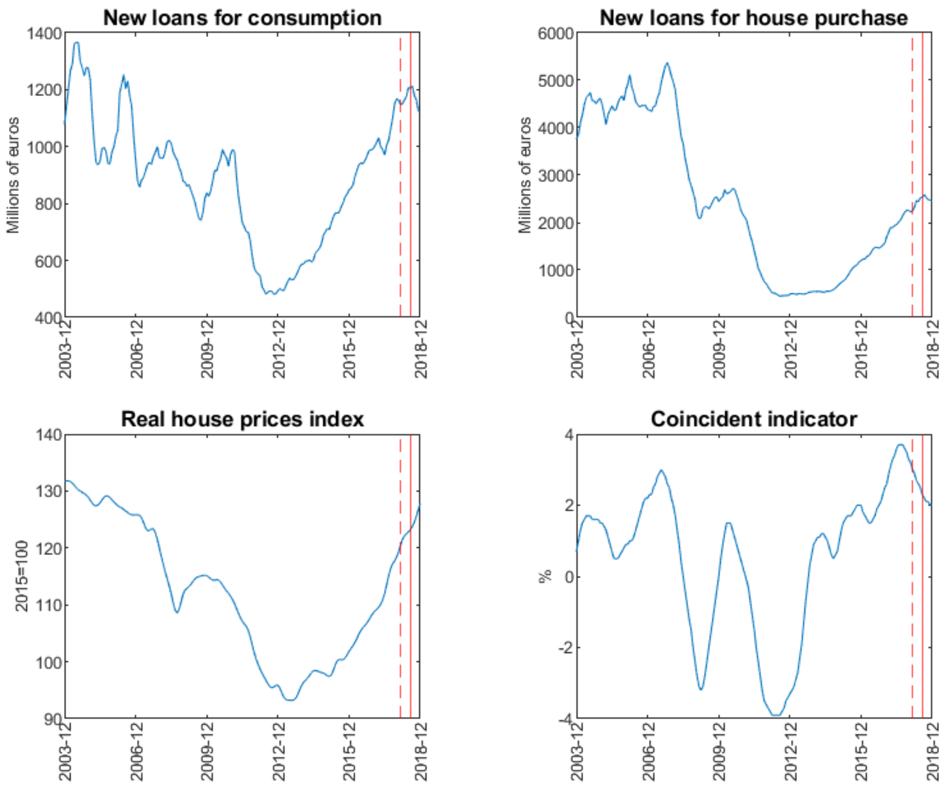

FIGURE 1: Endogenous variables

Sources: Banco de Portugal, INE and OECD. Note: Dashed line stands for the announcement date of the Recommendation and the solid line stands for the implementation date of the Recommendation.

5. Figure B.1 in appendix B presents the evolution of the control variables over our sample.

The period following the global financial crisis and the sovereign debt crisis was characterized by a gradual recovery of economic activity and of labour market conditions, reflected in a decreasing unemployment rate and increasing wage growth, which allowed for a recovery of disposable income of households. The recovery of the Portuguese economy was accompanied by a rebound of new loans to households, which have steadily increased since 2014 until the second half of 2018. However, the volume of new loans for house purchase by then was still far from the level observed before the global financial crisis. The recovery of new loans took place in a context of accommodative monetary conditions and increasing competition in the banking sector, which contributed to a narrowing of interest rates spreads on new loans granted to households and a relative easing of credit standards. Coincidently, after a period of gradual decline towards a historical low in 2013, the house price index rapidly increased towards pre-crisis levels. The upward momentum in house prices has accelerated since 2016 reaching double digit year-on-year rates of change.

In the first half of 2018, and even after the announcement of the Recommendation in February 2018, the volume of new loans granted to households continued its upward trajectory. New loans for consumption reached, in 2018M6, a year-on-year rate of change of 24.4%, a figure above the 90th percentile (22.4%) of the distribution of the rate of change, while the growth of new loans for house purchase stood at a year-on-year rate of change of 29.0%, which is above its historical median (9.5%) but far from the historical 90th percentile (55.2%). Following the implementation of the Recommendation the year-on-year rate of change of new loans for house purchase decreased, in a similar fashion as in the case of new loans for consumption, although in a less drastic way, remaining close to its median value (9.5% in 2018M12), whereas new loans for consumption reached negative values (-4.1% in 2018M12).

In 2018, house prices continued to grow at a rapid pace and, despite the slight deceleration observed between March and September, the year-on-year rate of change in house prices returned to an upward trajectory in October. Important drivers of these dynamics in house prices have been the improvement in household's income, the low interest rate environment and the easing on credit standards on new loans for housing (Banco de Portugal 2018). In particular, the persistent low interest rate environment increased the appeal of real estate investment in relation to the investment in alternative financial instruments. Additionally, in the beginning of 2018, signs of price overvaluation have emerged in the Portuguese housing market. These developments reflected an increasing importance of investment by non-residents, which increased significantly after 2014, and the demand of real estate by investors associated with tourism, especially for local accommodation.

3. Counterfactual exercise

The counterfactual scenario is constructed for the 6 months after the introduction of the Recommendation, that is, for the 2018M7 – 2018M12 period. In our view this evaluation period strikes a reasonable balance: if it was shorter we might have insufficient data to clearly identify the policy impact; if it was longer the methodology would likely produce less reliable results given that the difficulty in forecasting increases with the forecast horizon and that the probability of the variables of interest being affected by other shocks after the implementation of the Recommendation also increases over time.

The use of historical relationships to construct the counterfactual relies on the assumption that the Recommendation was the only relevant shock that affected the credit and housing markets, since its implementation. If other relevant shocks occurred, the difference between the counterfactual and the observed data would also reflect the presence of these additional shocks. In January of 2018, the Banco de Portugal issued a Notice introducing minimum requirements for assessing the creditworthiness of consumers. Both the Notice and the Recommendation have the common objective of promoting the access to sustainable financing by consumers. Nevertheless, and in contrast with the Recommendation, this Notice did not define concrete limits to specific credit standards. Therefore, it seems reasonable to assume that the Recommendation is more likely to have an effect on the volume of new loans granted to households than the Notice. To the best of our knowledge, there were no other pieces of regulation introduced in Portugal during the second half of 2018 that could affect, in a significant way, the credit and housing markets and thus contributing to the potential differences between the counterfactual and the observed data.

Figure 2 plots the counterfactual and the observed path of each endogenous variable. The BIC criteria suggests that 5 lags are appropriate, therefore the counterfactual values correspond to the median of the posterior predictive distribution of the estimated BVAR(5) model. The lower and upper bounds correspond to the 2.5th and 97.5th percentiles, respectively, of the posterior predictive distribution. If the observed values lie within the two percentiles, the difference between the observed values and their counterfactuals, which reflects the potential impact of the macroprudential policy measure, is negligible and comparable to common model forecast uncertainty. In other words, the difference is not statistically significant meaning that there is no evidence of an impact stemming from the policy introduction.

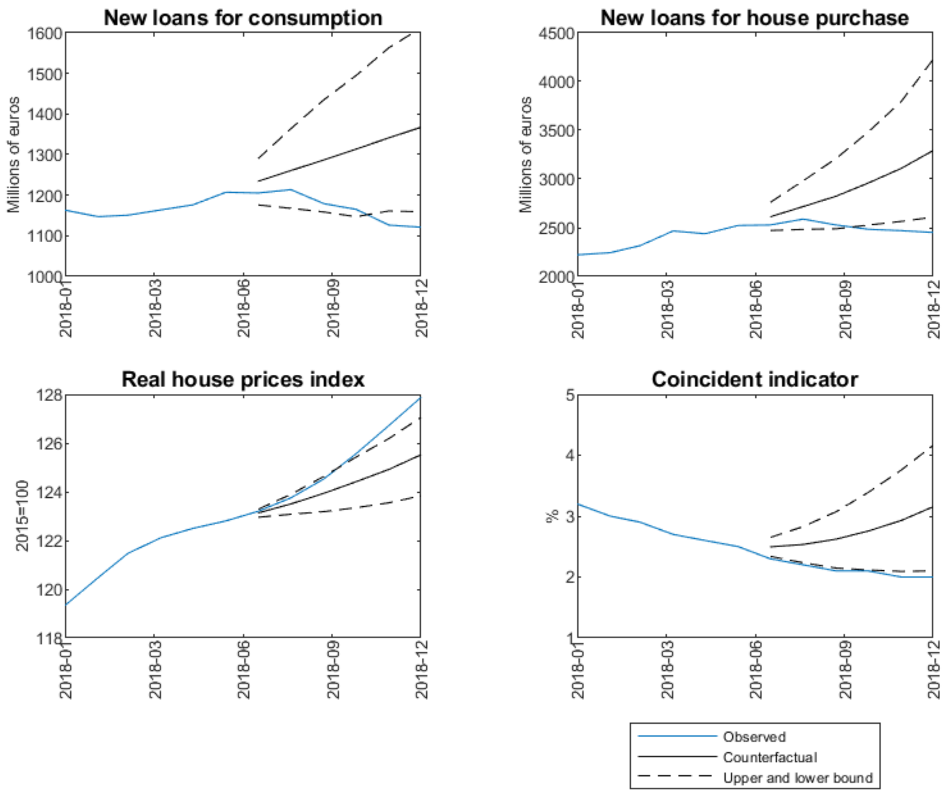

FIGURE 2: Counterfactual variables

Sources: Banco de Portugal, INE and OECD. Notes: Counterfactual corresponds to the median of the predicted posterior distribution given by a BVAR(5). Upper and lower bound are the 97.5th and 2.5th percentiles, respectively, of the same distribution.

The counterfactual suggests that, in a no-policy change scenario, new loans for consumption and for house purchase would have continued to increase. In contrast, the observed data shows that new loans lost steam in the second half of 2018, particularly in the case of new loans for consumption that even recorded negative year-on-year rates of change after October 2018. In the 3 months after the introduction of the policy measure, i.e., between July and end-September of 2018, the figures for new loans lie within the upper and lower bounds. In the following months until December 2018, both new loans for consumption and for house purchase lie outside the lower bound for the counterfactual, suggesting that the policy introduction curbed the growth of new loans in this period. Against this background, we may conclude that the Recommendation did not cause an immediate response of new loans. In fact, the evidence suggests that the adjustment in the dynamics of new lending only took place 4 months after the policy introduction. The delayed response of new loans may reflect initial operational adjustments that banks had to make to implement the limits imposed by the Recommendation. Additionally, according to Banco de Portugal (2019a, 2020) the evolution of new loans for house purchase in the first months after the introduction of the Recommendation reflected, in part, lending decisions for which borrowers' creditworthiness assessment was carried out several months before its entry into force.[6]

As for house prices, the counterfactual suggests that in a no-policy change scenario the upward momentum observed in the first half of 2018 would continue through the second half of the year, although at a slower pace. However, observed house prices are higher than in the counterfactual and the difference between the two time series increases over time. In fact, in the first months after the introduction of the Recommendation the house prices index lies within the 2.5th and 97.5th percentiles of the posterior predictive distribution and so the difference between the observed values and the counterfactual values is comparable to usual forecast uncertainty. After October 2018, the observed values lie outside the upper bound, which could suggest a positive and statistically significant impact of the policy introduction. However, stricter credit limits are expected to have a negative effect on the growth of house prices, even if this effect might only be clear in the long-run, as house prices tend to adjust slowly. In fact, several studies find that house prices tend to slow-down several months after the introduction of borrower-based measures (e.g. Ahuja and Nabar 2011 and Igan and Kang 2011). This leads us to infer that the positive statistically significant effect on house prices after October 2018 might reflect that the counterfactual is being affected by short-term factors that influence the housing market other than the introduction of the Recommendation. In fact, the Portuguese housing market has been particularly buoyant since the second half of 2017, reflecting not only the low interest rate and high liquidity environment but also the high dynamism of tourism and demand by non-residents. This recent increase of residential investment by non-residents, that do not borrow from the domestic credit market and, therefore, are not affected by the Recommendation, is documented in Banco de Portugal (2019b), where it is shown that residential investment by non-residents increased during 2018, in relation to investment by residents, while the percentage of transactions financed with domestic bank credit remained constant. Although we condition the counterfactual on the observed values of a set of control variables, including investment by non-residents, the model might not be able to account for the historically unprecedented buoyancy in the housing market in 2018, thus leading to an underestimation of the true counterfactual of house prices. The counterfactual reflects the expected trajectory of house prices based on the historical relations between the variables in the model. Thus, although the model is not specifically designed to evaluate the deviations of house prices from its fundamentals, we consider the results to be consistent with evidence of overvaluation of house prices in Portugal during 2018 as documented in Banco de Portugal (2019b), which seems to be particularly strong in the last quarter of that year. In particular, Banco de Portugal (2019b) present the results obtained from quantile regressions which suggest that real house prices grew above the estimated 90th percentile of the respective distribution

6. This could suggest using a date beyond July 2018 as the starting point for the impact assessment of the Recommendation. However, if the estimation sample included information from months in which the Recommendation was already implemented, the estimated counterfactual would not truly reflect a no-policy change scenario, raising identification issues.

during 2018. This evidence is comparable, to a certain extent, to the result obtained from our counterfactual analysis, as house prices are above the upper bound of the forecast which corresponds to the 97.5th percentile of the predictive distribution. Additionally, the short sample employed in the estimation of the model may also explain, at least in part, this result. In fact, the recovery observed since 2013 is the only period in the sample in which a sustained upward trend in house prices is observed. This may also contribute to an underestimation of the counterfactual for house prices.

The counterfactual for the coincident indicator suggests an acceleration of economic activity during the second half of 2018. In comparison, the "observed" coincident indicator has decreased over the same period. The difference between the counterfactual and the coincident indicator increases over time, suggesting that the introduction of the Recommendation might have implied lower economic activity. By introducing stricter criteria for borrowers' creditworthiness assessment, the Recommendation might have curbed the growth of new loans, which could have had a negative effect on household expenditure and, therefore, on economic activity. The upward trajectory of the counterfactual for the coincident indicator reflects, in part, the growth in new loans in the estimated no-policy scenario (in contrast to the observed values), which is amplified by the autoregressive component of the model. However, the counterfactual for the coincident indicator is very close to the lower bound, meaning that the difference between the coincident indicator and the counterfactual is comparable to the common forecast error of the model.

Therefore, we do not find strong evidence that the introduction of the Recommendation had a significant impact on economic activity in the 6 months following its introduction. It is worth noting that although BVAR models tend to have good forecast performance over short forecast horizons as a result of their flexibility and simple (linear) structure, our model is not tailored to forecast the evolution of economic activity. This implies that accumulation of forecast errors, that occur when forecasting h periods ahead in an autoregressive framework, is especially relevant for this variable since there is a larger uncertainty in comparison to the other endogenous variables.

A number of robustness checks were conducted. In particular it was examined if the results are influenced by potential structural breaks in the data. In order to address this issue, we estimated the model with first differenced data which robustifies, to a certain extent, against structural breaks. The results based on the resulting counterfactuals were qualitatively similar to the ones obtained in the main exercise (see Figure C.1 in the appendix C).

4. Conclusions

We estimate the ex-post and short-term impact of the introduction of a borrower-based measure in Portugal on new loans granted to households, house prices and economic activity. For this purpose, we estimate a counterfactual scenario for the 6 months following the policy measure introduction, using a BVAR(5) model. The counterfactual provides a description of the evolution of the variables of interest in a scenario that tries to mimic the absence of the policy change.

The data suggest that new loans granted to households, both for house purchase and consumption, slowed down after the introduction of the Recommendation. The counterfactual suggests that the Recommendation contributed to this slowdown of new loans granted to households, although this impact is only statistically significant 4 months after its introduction.

As for the short-term impact of the Recommendation on house prices, the results are less clear as the observed values are above the estimated counterfactual and the upper bound for the forecast values. The difference between the observed house prices and the estimated counterfactual are unlikely to reflect the introduction of the Recommendation as, according to the existing literature, tighter credit standards are expected to slow down house prices growth. Intrinsic short-term housing market shocks and the historically unprecedented buoyancy in the Portuguese housing market, mainly fuelled by investment by non-residents, might be affecting these results.

Finally, we do not find evidence that economic activity was influenced by the Recommendation in the 6 months following its implementation.

Appendix A: BVAR model estimation and specification

The set of prior beliefs associated to the model parameters (θ) are explicitly defined in the form of a prior distribution for the model parameters, $g(\theta)$. In the standard VAR(p) setting, the parameters are usually grouped in two blocks, one regarding the slope coefficients β, and another associated with the covariance matrix Σ, so that $\theta = (\beta, \Sigma)$. The information contained in the observed sample is summarized in the data likelihood function $f(y|\theta)$. Then, the posterior distribution of the model parameters, denoted by $g(\theta|y)$, can be obtained by combining the prior beliefs with the information contained in the sample via the Bayes theorem, which states the joint density as

$$f(\theta, y) = g(\theta|y)f(y) \tag{A.1}$$

hence

$$g(\theta|y) = \frac{f(y|\theta)g(\theta)}{f(y)} \Longrightarrow g(\theta|y) \propto f(y|\theta)g(\theta) \tag{A.2}$$

When setting the prior beliefs one usually specifies the prior distribution of each block of parameters, $g(\beta)$ and $g(\Sigma)$, instead of the respective joint distribution $g(\theta)$. In order to simplify the definition of $g(\theta)$, the model parameters are assumed to be independent so that

$$g(\theta) = g(\beta, \Sigma) = g(\beta) \times g(\Sigma) \tag{A.3}$$

Similarly, we are interested in evaluating the posterior distribution of each block of parameters.

One of the simplest methods to specify the prior distribution of the VAR(p) parameters is the Minnesota (or Litterman) prior (Doan *et al.* 1984). The main idea behind this strategy is to shrink the slope estimates towards a multivariate random walk model. In this setting the covariance matrix Σ is assumed to be known. A convenient way to define Σ is to simply use the OLS covariance matrix estimate from the VAR(p) model. Therefore, in order to obtain the posterior distribution of the parameters $g(\theta|y)$ we only need the following elements: the data likelihood function $f(y|\beta, \sigma)$ and the prior distribution $g(\beta)$ for β.

The data likelihood function $f(y|\beta, \sigma)$ has a Gaussian form, as the error term is assumed to follow a multivariate normal distribution $E \sim N(0, \Sigma)$. The slope parameters are assumed to follow a multivariate random walk model so that the prior distribution for β can be expressed as $\beta \sim N(\beta_0, \Omega_0)$. The prior distribution of β is governed by the so-called hyperparameters β_0 and Ω_0, which are specified as follows:

- β_0 is oriented by the prior belief that each endogenous variable can be characterized by a random walk. Thus, the first autoregressive coefficients of the endogenous variables should be set to one and coefficients of further autoregressive lags, cross-variable lags and control variables should be set to zero. Following this strategy, β_0 will simply translate into a vector of ones and zeros.
- to identify Ω_0 we use the following principles:

- the covariance between the elements in vector β is zero so that Ω_0 is a diagonal matrix;
- coefficients associated to the most distance lags are assumed to be close to zero and we express this prior belief by assigning a smaller variance to coefficients associated with further lags;
- The prior belief that the coefficient is close to zero should be stronger for the coefficients associated with cross-variable lags;
- No prior information is available for the control variables (control variables) and, therefore, we set the variance associated with these coefficients to infinity.

Therefore, using this information, the elements of Ω_0 can be summarized as follows:

$$\sigma^2_{a_{ij}} = \begin{cases} \left(\frac{\lambda_1}{l^{\lambda_3}}\right)^2 & if \quad i = j \\ \\ \left(\frac{\sigma_i^2}{\sigma_j^2}\right)\left(\frac{\lambda_1 \lambda_2}{l^{\lambda_3}}\right)^2 & if \quad i \neq j \end{cases}$$

where λ_1 and λ_2 are parameter that control the overall tightness of the autoregressive and cross-variables coefficients, respectively. λ_3 controls the speed at which the coefficients of further lags converge to zero, and l is the number of the lag. Finally, σ_i^2 is the i^{th} diagonal element of the VAR(p) covariance matrix, which can be replaced by the respective OLS estimate. In practice, hyperparameters are selected through a grid-search procedure to find the values that minimize a measure of fit of the model to the data.

Appendix B: Control variables

Figure B.1 plots the control variables over the period considered in the sample. Residential investment has been increasing since 2012, both from residents and non-residents. In 2018, residential investment continued to increase having accelerated in 2018m12 relatively to 2018M6. This happened in a context of historically low interest rates, largely influenced by monetary policy, as reflected by the 12-month Euribor graph, and a deceleration of the Euro area gross domestic product, after the recovery experienced after the global financial crisis and the sovereign debt crisis in some European countries.

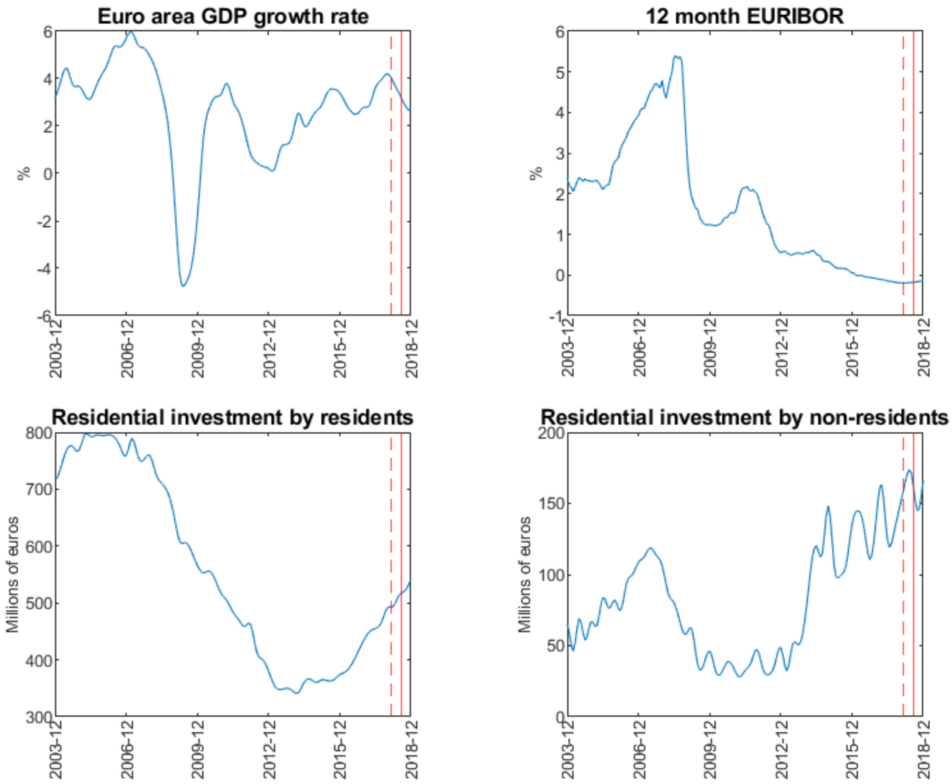

FIGURE B.1: Control variables

Sources: Banco de Portugal, INE, OECD and ECB. Note: Dashed line stands for the announcement date of the Recommendation and the solid line stands for the implementation date of the Recommendation.

Appendix C: Counterfactual estimated with first differenced data

In order to account for possible structural breaks in the data, we estimated the BVAR model on first differenced data and computed the counterfactual from this estimated model. Differentiation robustifies the analysis against structural breaks and can improve the forecast ability of the model. It can be seen from Figure C.1 that the counterfactual estimated with the data in levels ("Counterfactual - levels") and from the model estimated with first differenced data ("Counterfactual – 1st differences) are very similar. In particular, the sign of the estimated effect of the introduction of the macroprudential measure appears to be robust when estimating the model in first differences. Regarding the results on new loans for consumption and house purchase, the distance between the counterfactual (both with levels and differenced data) to the observed series increases in the months at the end of the forecasting period. Therefore, we consider that this exercise supports the conclusion of a more pronounced reduction of the volume of new loans 4 months after the policy implementation.

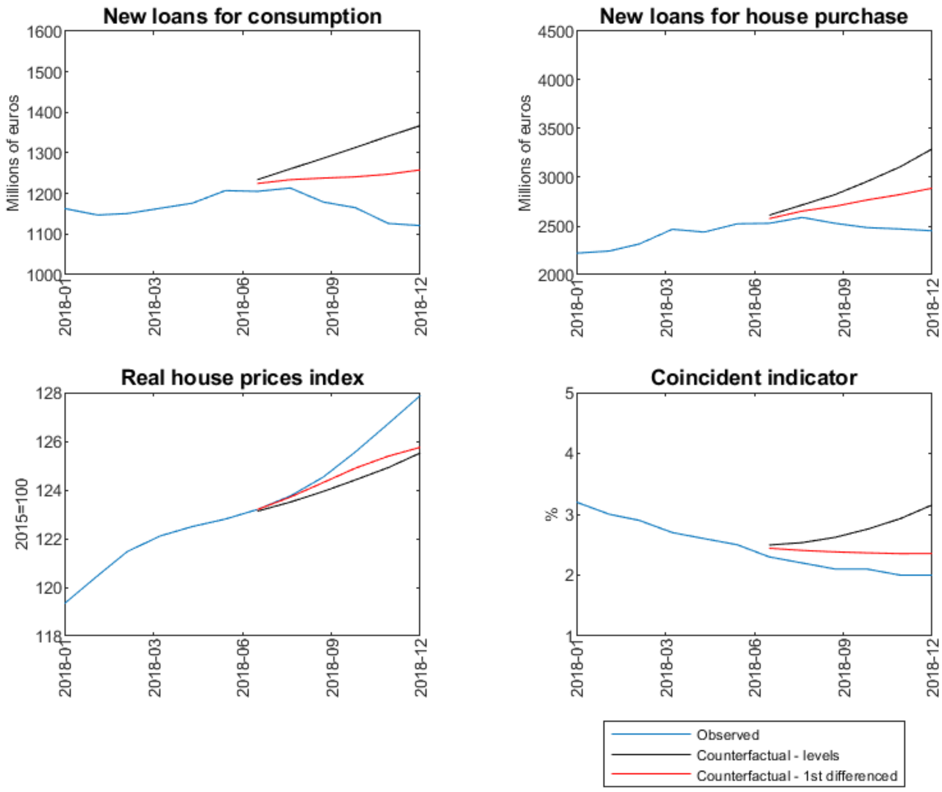

FIGURE C.1: Counterfactual estimated with the data in levels and first differences

Sources: Banco de Portugal, INE and OECD. Notes: Counterfactual corresponds to the median of the predicted posterior distribution given by a BVAR(5).

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