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MACROPRUDENTIAL POLICY, MONETARY POLICY AND EUROZONE BANK RISK

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Macroprudential policy, monetary policy and Eurozone bank risk*

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Abstract

We investigate the impact of macroprudential policy on the risk and return profile of Eurozone banks between 2008 and 2018, conditioning on the stance of monetary policy. Using local projections, we find that a tightening in macroprudential policy increases financial stability by curbing credit growth and increasing the resilience of the banks. With respect to the policy mix, we show that tight macroprudential and monetary policies reinforce each other. But even when monetary policy is accommodating, macroprudential policy is found to be effective in deterring excessive bank risk taking. However, we also document adverse consequences for bank franchise values.

Keywords: Euro Area banks, macroprudential policy, monetary policy, inverse propensity score matching, local projections, bank risk profile

JEL codes: C23, E52, E61, G21, G28.

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1 Introduction

Macroprudential policy is in vogue. The Great Financial Crisis amply demonstrated that microprudential regulation was insufficient to maintain the stability of banks. As a result, macroprudential policy has gained prominence in tackling the systemic risk of the banking industry. Whereas the objective of microprudential policy is to limit bank idiosyncratic risk, macroprudential policy attempts to improve financial stability from a systemic perspective (see e.g. Crockett, 2000, Borio, 2003 and Caruana, 2010). In the Euro Area, various macroprudential tools, both bank-based and borrower-based, have been introduced in a period characterized by the active use of monetary policy tools by the ECB. And while monetary policy and macroprudential policy have their own objectives, i.e. price stability and financial stability, there are several channels through which one policy can influence the objective of the other. This naturally raises an important policy question: is the transmission of macroprudential policy different conditional on the stance of monetary policy? The interactions can enhance or reduce the effectiveness of each policy in achieving its objective and may therefore suggest the need for coordination (Smets, 2014).

We empirically analyze this question for the euro area banking system. In particular, we examine whether or not the effectiveness of macroprudential policy is influenced by the stance of ECB monetary policy. To do this, we perform an in-depth investigation of the transmission of macroprudential policy shocks to the banks in the euro area. Our empirical analysis proceeds in different stages. First, we investigate the macroprudential transmission channels by assessing the impact of macroprudential policy on a broad set of bank risk and return profile variables that capture the resilience of the banking system. Second, as different types of macroprudential measures are expected to produce different effects depending on a bank's business model, we investigate whether the transmission of macroprudential policy is heterogeneous across different bank business models. Ultimately, we interact the macroprudential policy shock with our measure of the monetary policy stance to understand how macroprudential policies transmit to the banks' risk and return profile. We focus on the behavior of Euro Area banks from 2008 to 2018, which is the period characterized by different stages of conventional and unconventional monetary policy by the ECB and which coincides with the introduction of various types of macroprudential policy in euro area countries. Throughout the empirical analysis we use the local projections framework of Jordà (2005) which allows us to visually assess how the banks' risk and return profile is affected by macroprudential and monetary policy shocks, their interaction,

whether or not these responses differ across banks and the persistence of these effects over time.

We aim to contribute to the literature in different ways. First, we use granular bank-level data and incorporate a wide range of bank risk and return profile variables constructed with both accounting and market data, which distinguishes us from papers that use a limited set of bank variables. Second, for the construction of a macroprudential index we make use of a new database collected by experts at the ECB and national banks. This MacroPrudential Policies Evaluation Database (MaPPED) contains information on almost 2000 macroprudential actions taken in 28 member states of the European Union. The database differs from other databases (for example Cerutti et al. (2017) and Lim et al. (2011) among others) since it not only indicates the activation of a certain policy tool, but it also tracks the tool over time by including, for example, changes in the level or the scope of the tool. Also, where other databases have a rather limited tool coverage, this database contains information on 53 different types of policy tools. The database ensures the comparability across measures and across countries which is one of the major drawbacks when using other existing databases (Budnik and Kleibl, 2018). We assess the impact of macroprudential policy on a set of bank risk and return profile measures using a novel identification strategy that only recently has been used in economics to assess the effectiveness fiscal policy (Jorda and Taylor, 2016) and macroprudential policy (Richter et al., 2018; Alam et al., 2019). More specifically, we use the inverse propensity score weighting methodology as an identification strategy to rerandomize the sample of the treatment and the control group which allows us to mitigate endogeneity concerns. Third, to construct the monetary policy stance, we estimate a structural vector autoregression (SVAR) to extract an exogenous monetary policy shock. This monetary policy shock is identified by assuming that its variance increases on days on which there is a monetary policy announcement. This 'identification-through-heteroskedasticity' approach yields monetary policy shocks that account for the prevailing macroeconomic and financial markets conditions, which determine the behavior of banks and the market assessment of their risk and return profile. Fourth, we add to the extant literature by exploring the interaction between monetary policy and macroprudential policy. Evidence concerning these interactions is rather limited and mainly comes from theoretical (DSGE) modelling rather than empirical analysis. In this paper we complement the literature with an in-depth empirical analysis of how different macroprudential policies affect the banking system and how they interact with monetary policy in the euro area.

Our main findings can be summarized as follows. Considered in isolation, we confirm that macro-

prudential policy is effective in restraining bank risk, as intended by the macroprudential authorities. Tightening macroprudential measures are typically associated with less lending and lower bank asset risk and these features translate into lower overall bank risk, both accounting-based and market-based. However, the downside is that the announcement of macroprudential tools is accompanied by lower bank profitability over the projection horizon which indicates that imposing constraints on banks causes lower current and future bank profitability. When considering the banks' business model, we find that for both lending and profitability the effects are more pronounced for retail banks compared to their non-retail counterparts. This is not unexpected since banks with a retail profile are most active in traditional lending, which is the focus of macroprudential measures targeting credit growth. The negative consequences on profitability are also more pronounced for retail-oriented banks, which may affect their future viability.

Ultimately, we assess whether the effectiveness of macroprudential policy with respect to bank risk and return profiles is different conditioning on the monetary policy stance. We find that macroprudential policy and monetary policy push credit growth in the same direction, i.e. they reinforce each other. In other words, the effectiveness of macroprudential policy with respect to bank credit growth is stronger when monetary policy is also in a tight phase. Conversely, when macroprudential policy is tight but monetary conditions are accommodating, loan growth increases, suggesting that the transmission of macroprudential policy to credit growth is affected by the presence of loose monetary policy. Interestingly, while accommodating monetary policy may entail incentives for banks to take more risk, our results indicate that macroprudential measures were sufficiently strong to deter banks from excessive risk taking. In other words, macroprudential policy succeeds in maintaining bank stability also in periods of monetary accommodation. Yet, there is an important downside: we observe a marked deterioration of the banks' market-to-book value as a reflection of the investors' conviction that low for long interest rates ultimately compress bank interest margins and put their profitability and franchise value under stress. Our conclusion is that the combination of restrictive macroprudential policies and prolonged monetary accommodation may turn out to be detrimental for bank health and, ultimately, financial stability.

Our main findings are corroborated when we estimate the monetary policy stance with a Taylor rule or when we use the 'identification-through-external-instruments' approach. When we consider the impact of specific macroprudential policy tools, we find that credit growth measures, such as

loan-to-value ratios, have an immediate and stronger negative impact on loan growth compared to liquidity regulation or measures aimed at the resilience of banks, such as capital regulation. However, we also find evidence for risk-shifting behavior by banks confronted with targeted credit measures: banks increase the riskiness of the loan portfolio in response to credit constraints. In trying to comply with the rules, these banks may engage in riskier activities by, e.g., shifting to more risky corporate lending or securities.

The paper proceeds in the following way. In section 2 we review the extant literature, analyse the transmission channels of macroprudential policy and develop our hypotheses. Section 3 describes the empirical setup we use to assess the effectiveness of macroprudential policy, both unconditional and conditional on the stance of monetary policy. Section 4 presents the data and the selection of the sample. In section 5 we analyze the empirical results followed by several robustness checks in section 6. Section 7 concludes.

2 The transmission of macroprudential policy

Monetary and macroprudential policies are intended to modify banks' behaviour by constraining credit supply and demand. Hence, both policies may affect banks through similar transmission channels. The question thus arises how they may influence each other's effectiveness in reaching their respective objectives. The interaction between both policies can either strengthen or weaken the effectiveness of each policy in achieving its goal. In this paper we assess the impact of macroprudential policy and investigate whether or not the transmission is different conditional on the stance of monetary policy.

Macroprudential policy actions are intended to affect the balance sheet of financial institutions and to enhance financial stability. For example, banks may respond to a tightening in capital requirements by issuing more equity, by increasing retained earnings, by deleveraging or de-risking. All of these strategies should increase the loss absorbing capacity of the banks and create an extra buffer in the case of unexpected losses. Liquidity-based tools force banks to hold more liquid assets or increase long-term funding which increases the resilience of banks to unforeseen liquidity shocks. Banks can also react to tighter liquidity regulations by decreasing their lending portfolio which also affects their resilience to adverse conditions. Borrower-based tools such as loan-to-value ratios or debt-to-income ratios affect the lending capacity of banks and should reduce the probability of default of the

borrowers, which improves the stability of the bank. Macroprudential tools such as limits on certain exposures or higher risk weights on specific asset classes impact the loan supply and make banks less sensitive to shocks in, e.g., real estate markets. All these transmission channels decrease the banks' risk profile, which should limit the occurrence of systemic crises.

Existing empirical work shows that macroprudential policy is capable of smoothing the financial cycle. Lim et al. (2011) evaluate the effectiveness of different macroprudential instruments on credit growth, systemic liquidity, leverage, and capital flows. They use IMF survey data containing information on macroprudential instruments used in 49 countries during a 10-year period from 2000 to 2010. They find that many of the instruments used are effective in reducing procyclicality. Shim et al. (2013) investigate the impact of macroprudential tools on housing credit and housing prices using a database for policy actions covering 60 economies worldwide from 1990 to 2012. The authors find evidence that mainly the debt-service-to-income requirements and housing-related taxes can be used as tools to restrain housing credit growth. In contrast, supply-side credit policies such as risk weights and provisioning requirements had no significant impact on housing credit. Cerutti et al. (2017) use an IMF survey, Global Macroprudential Policy Instruments (GMPI), to investigate the impact of 18 different policy instruments on credit growth in 119 countries over the period 2000 to 2013. They find that the policy tools are effective in reducing credit growth, yet the effects are more pronounced in emerging economies. Akinici and Olmstead-Rumsey (2018) use a combination of IMF survey data, BIS data and information received from national central banks and financial authorities to analyse the influence of macro policies on credit growth and housing prices. Using a dynamic panel setting they find that tightenings in macroprudential tools are associated with lower credit growth and housing prices. Igan and Kang (2011) make use of a regional database to examine the effect of loan-to-value and debt-to-income limits on house price dynamics, residential real estate market activity, and household leverage in Korea. They find evidence that loan-to-value and debt-to-income tools are indeed associated with both a decline in house prices and a drop in the number of transactions. Dell'Ariccia et al. (2016) find that, for a large cross-country dataset covering 170 countries over the period 1970–2010, macroprudential tools are effective in reducing the emergence of credit booms and the costs associated with credit busts, in contrast to monetary and fiscal policies. Meuleman and Vander Venet (2020) investigate whether macroprudential policy is able to support financial stability by tackling the interconnectedness of banks for a sample of Eurozone banks between 2000 and 2017.

They find that liquidity and capital regulation is able to address the systemic linkage of banks while credit growth tools and exposure limits have more impact on the individual risk of banks. In general, most empirical studies conclude that macroprudential policy tools achieve their stated objective, although some tools appear to be more effective than others.

Evidence on the interactions between monetary policy and macroprudential policy is still scarce and mainly comes from theoretical (DSGE) modelling rather than empirical analysis and focuses on whether the macroprudential and monetary policymakers should cooperate or not (see for example Angelini et al. (2014), Paoli and Paustian (2017) and Gelain and Ilbas (2017)). Most papers find that after a financial shock, when policies cooperate, both types of policy should work in the same direction, i.e. they complement each other. This paper empirically adds to this discussion as we investigate whether or not the effectiveness of macroprudential policy is affected by the stance of monetary policy in the Euro Area. Rubio and Carrasco-Gallego (2014) analyze the interactions between a macroprudential loan-to-value rule and a monetary policy Taylor rule in a DSGE model with housing and collateral constraints. They find that the actions of both policies unambiguously improve the stability of the system. Martinez-Miera and Repullo (2019) find that both tight macroprudential policy, in the form of binding capital requirements, and tight monetary policy individually reduce risk-taking, however, when the two policies are interacted, bank risk-taking increases as the transmission of monetary policy to the loan rates is affected by the presence of binding capital regulation. With respect to empirical evidence, Aiyar et al. (2016) find that tightening monetary policy and increasing banks' capital requirements both have negative effects on bank credit supply, and that there is no interaction between changes in monetary policy and changes in capital requirements. On the other hand, Tressel and Zhang (2016) use an interaction term between the monetary policy stance and a LTV indicator and find that LTV constraints tend to be more effective in containing credit growth and house price appreciation when monetary policy is loose. Gambacorta and Murcia (2019) use granular credit registry data of five Latin American countries and find that macroprudential policy and monetary policy reinforce each other by pushing in the same direction. David et al. (2019) confirm these results as they find benefits of synchronisation between macroprudential and monetary policies using a panel data setting for a sample of 37 emerging and advanced economies.

3 Methodology

The overarching research question of this paper is to investigate the effectiveness of macroprudential policy conditional on monetary policy. To tackle this question, our empirical investigation proceeds in two stages. We first focus on the standalone effect of macroprudential policy on the bank risk and return profile variables, we identify macroprudential actions based on the MaPPED database and we explain how we use the inverse propensity score approach to analyze the impact of macroprudential policy on bank risk and return profiles. We also check potential heterogeneous effects of these macroprudential measures across bank business models (in subsection 3.1). Second, we identify the monetary policy stance based on an identification-through-heteroskedasticity approach in order to investigate the impact of a macroprudential shock across different monetary policy regimes (in subsection 3.2).

3.1 Macroprudential policy and the bank's risk and return profile

As a first step in the analysis we need information on the macroprudential actions that have been initiated in the Eurozone. We use the granular information available in the MacroPrudential Policies Evaluation Database (MaPPED) which has been collected by experts at the ECB and the national central banks (Budnik and Kleibl, 2018). MaPPED provides details on 1925 macroprudential (or similar) policy actions between 1995 and 2018 in the 28 member states of the European Union. The tools are subdivided in 11 categories: capital buffers, lending standards, maturity mismatch tools, limits on credit growth, exposure limits, liquidity rules, loan loss provisions, minimum capital requirements and risk weights, leverage ratio, and other measures (this category contains mainly crisis-related measures and resolution tools). The MaPPED survey is designed in such a way that respondents can only choose from a closed list of policy tools, in contrast to open-text questionnaires as in Lim et al. (2011) or the GMPI. These features ensure that the comparability across measures and across countries is maintained which is one of the major drawbacks when using other existing databases (Budnik and Kleibl, 2018).

MaPPED tracks every measure over time, indicating not only the activation date, but also changes in the scope or the level of the measure over time, as well as the deactivation of the measure. We use the announcement date of each tool to analyse how banks react to the macroprudential policy changes

using impulse response functions over a horizon of 8 quarters.¹ Each policy action is classified as a loosening action, a tightening action or as an action with an ambiguous impact. We construct an overall indicator of macroprudential policy based on this MaPPED database. First, individual policy instruments are each coded as 1 in the quarter they are announced and zero otherwise. An activation and a change in the scope or level of a tool are all coded as 1. Measures with an ambiguous impact are conservatively coded as 0. An overall macroprudential policy indicator is the sum of the scores on all 11 individual policies.

In terms of establishing the effect of macroprudential policy actions on the banks' risk and return profile, the main challenge is tackling the endogeneity issue. Reverse causality can be a problem in our context because macroprudential policy actions are more likely to be tightened during periods of high credit growth and increasing bank risk. Therefore, estimations that do not address the issue may be subject to a measurement error. We employ an inverse propensity-score weighted (IPW) estimator specifically designed for our purposes. Propensity score methods have been originally used in biostatistics and medicine (see for example Austin (2009) or Rosenbaum and Rubin (1983) among others). More recently, they have been applied in economics to assess the effectiveness fiscal policy (Jorda and Taylor, 2016) and macroprudential policy (Richter et al., 2018; Alam et al., 2019). The IPW estimator alleviates endogeneity issues by penalizing those observations that are likely to be affected by reverse causality. More specifically, an IPW estimator gives more weight to those observations that are difficult to predict based on a set of macro variables that are used by regulators to initiate macroprudential policy tools, and less weight to those macroprudential actions that are easy to predict based on the macro variables. The methodology is particularly well-suited to analyse macroprudential policy since the macroprudential regulator indeed uses indicators (for example the credit-to-gdp gap for the initiation of the countercyclical buffer or housing credit/prices for credit growth measures) to initiate macroprudential policy.² In practice we first specify a logit model at

¹We use the announcement date rather than the enforcement date as we hypothesize that market participants and banks immediately respond to changes in the macroprudential policy stance in the quarter of announcement, even before the tool is in force.

²The IPW methodology comes close to the propensity score matching technique as used in Forbes et al. (2015). We believe however that using the IPW technique results in more reliable results than when we use the propensity score matching technique because we would lose a lot of observations as we would only match each treated observation with one matched control observation. The matching technique does not take into account other control observations, and the control group is shrunk down to the same size as the treatment group. In contrast to the propensity score matching technique, the IPW matching occurs in both directions: from control to treated and from treated to control. That is, each observation is given weight of the inverse of the probability of the treatment they actually got so we do not lose observations. Intuitively, treatment cases that resemble the controls are interesting and given more weight, and control cases that look like they should have got the treatment also receive a higher weight.

the country level to estimate the probability that a certain macroprudential policy tool is activated. Let $D_{i,t}$ be a tightening dummy that takes on a value of 1 when a macroprudential policy action is announced in a certain quarter (or when multiple actions are announced) and zero otherwise:

$$\log \left(\frac{D_{i,t} = 1 | Z_{i,t-1}}{D_{i,t} = 0 | Z_{i,t-1}} \right) = \alpha_i + \lambda_{year} + \beta Z_{i,t-1} + \varepsilon_{i,t} \quad (1)$$

$Z_{i,t-1}$ is a vector of macroeconomic controls lagged one quarter. We include the country's total bank loan growth, the change in housing prices, the growth in household debt to GDP, GDP growth, the VSTOXX and the ECB policy rate. We also include country and year fixed effects. We refer to the probability of a tightening as the propensity score and its estimate from Equation 1 is denoted by $\widehat{p}_{i,t}$.

In a second stage, we fit the probabilities for the logit model at the country level using regression weights given by the inverse of $\widehat{p}_{i,t}$. Weighting by the inverse of the propensity score puts more weight on those observations that were difficult to predict and thereby re-randomises the treatment. In our application, this implies putting more weight on macroprudential tightenings that were considered as a surprise based on observed data, and putting less weight on those tightenings that could be predicted. We convert the country probabilities to the bank level setting by assigning each bank situated in a specific country the same probabilities. With the fitted probabilities we can now estimate the cumulative responses of a shock in the macroprudential index on the change in the bank risk and return profile measures between 2008 and 2018 with the following local projections model using weighted least squares (WLS) as in Richter et al. (2018) and Alam et al. (2019):

$$\Delta y_{i,j,t+h} = \alpha_i^h + \gamma_t^h + \Lambda^h D_{j,t} + \sum_{k=0}^K \theta_k^h Bank_{i,t} + \sum_{l=0}^L \psi_l^h Macro_{j,t} + \varepsilon_{i,t+h} \quad (2)$$

$\Delta y_{i,j,t+h}$ denotes the percentage change in the risk and return profile variables for bank i in country j between time t and $t+h$. $D_{j,t}$ corresponds to the tightening dummy in country j at time t . α_i^h and γ_t^h denote the bank fixed effects and the time fixed effects, respectively. The coefficient of interest is Λ^h which captures the impact of a macroprudential change at time t on the bank risk and return profile variables at horizon h .³ We expect this coefficient to be negative for the banks' risk variables since

³We argue that the variables on the right-hand side are predetermined and they serve as a benchmark so that $\Delta y_{i,j,t+h}$ can be seen as the deviation in Y from the expectation at time $t+h$ based on the information available at time $t-1$. If this would not be the case, the deviation in Y can also be due to (endogenous) changes in the covariates, which we want to avoid. This approach only allows us to determine the direct impact of a shock to $\Delta y_{i,j,t+h}$ rather than indirect effects through other variables. More specifically, the IRF's thus only capture the impact of a macroprudential shock at time 0,

macroprudential policy tools are aimed at increasing bank stability. The variable *Bank* represents a vector of bank business model characteristics. *Macro* correspond to the macroprudential policy indicators which we also use in the propensity score model. We include the country's loan growth, the change in housing prices, the growth in household debt to GDP and GDP growth. The weights that are used in this weighted least squares estimation are defined by $w_{i,j,t} = \frac{D_{j,t}}{\bar{p}_{j,t}} + \frac{1-D_{j,t}}{1-\bar{p}_{j,t}}$, where we truncate $w_{i,j,t}$ at 10 to avoid extreme weights. For all the impulse responses in the analysis, we use a horizon of 8 quarters.

Different types of macroprudential measures are expected to produce different effects depending on a bank's business model. Therefore we allow for heterogeneous impulse responses across bank types. Several papers have attempted to classify banks into business models based on various statistical approaches, typically yielding between 4 and 7 business model types (see Kok et al., 2016, Farnè and Vouldis, 2017 and Roengpitya et al., 2017). However, the differences between the business models are often qualitative in nature. Therefore we opt for a parsimonious subdivision of the banks based on a limited number of observable bank balance sheet indicators. To do this, we perform a factor analysis on the bank characteristics $Bank_{i,t}$ (the loan ratio (LTA), the ratio of customer deposits to total liabilities (DEP), the ratio of total equity to total assets (CAP), the share of non-interest income in total income (DIV) and bank size (SIZE)). If there is common variance, this will be reflected by factors associated with eigenvalues above 0. The higher the eigenvalue, the more the factor is able to explain common variance. This implies that factors with low eigenvalues are less likely to reflect the broad common strategies that we relate to bank business models. Table 1 presents the results of the factor analysis.

[Table 1 about here.]

The first factor, which explains 63% of all variation, is associated with a retail-based strategy. Therefore we label this factor as *RETAIL* as it is a vector that captures the *retailness* of a bank.⁴ It positively relates to the loan, deposit and capital ratios, but is negatively related to size and income diversification. The higher the factor score, the more retail-oriented the bank is. The subdivision in retail versus non-retail banks has intuitive appeal for our research question since many macroprudential measures are targeted to a specific type of bank (e.g., countercyclical capital buffers or lending

assuming all else equal over each horizon of the IRF.

⁴We acknowledge that the labeling of factors is always somewhat subjective. In this paper, the choice for the label follows Mergaerts and Vander Vennet (2016).

restrictions in the form of LTV caps are designed to primarily affect retail banks). We use the first factor obtained through the factor analysis in interaction with the macroprudential policy shock to assess heterogeneous effects across banks. Concretely, we estimate the following local projections model:

$$\begin{aligned} \Delta y_{i,t+h} = & \alpha_i^h + \Psi^h Shock_t + \chi^h BBM_{i,t} + \Pi^h Shock_t \times BBM_{i,t} + \sum_{k=0}^K \omega_k^h Bank_{i,t} \\ & + \sum_{l=0}^L v_l^h Macro_{i,t} + \varepsilon_{i,t+h} \end{aligned} \quad (3)$$

$\Delta y_{i,t+h}$ denotes the percentage change in the risk and return profile variables for bank i between time t and $t+h$. $Shock_t$ corresponds to the macroprudential shock. α_i^h are the bank fixed effects. When we estimate the impact of macroprudential policy we also include time fixed effects and estimate the model with weighted least squares with weights defined by $w_{i,j,t} = \frac{D_{j,t}}{p_{j,t}} + \frac{1-D_{j,t}}{1-p_{j,t}}$. $BBM_{i,t}$ stands for the first factor of the factor analysis which distinguishes between retail and non-retail banks. The differential impact between retail and non-retail banks can then be calculated as the partial derivative of the bank risk and return profile variables with respect to the shock.⁵

3.2 Interactions between monetary and macroprudential policy

Ultimately, we want to investigate the impact of macroprudential shocks conditional on the stance of monetary policy. Macroprudential policy is implemented by national authorities, while monetary policy is determined at the ECB level. Hence, national macroprudential policies have to take the stance of monetary policy as given. The important policy issue is whether or not the effectiveness of macroprudential policy depends on monetary policy conditions. For the identification of the monetary policy stance in the Eurozone in the post-2008 period, we cannot use the policy rate because of the zero lower bound constraint. Similarly, the ECB balance sheet cannot be used because some impor-

⁵In an estimation setup with interaction terms, the full effect is measured as the partial derivative of the bank risk and return profile variables with respect to the shock, which boils down to the sum of the standalone effect and the coefficient on the interaction term times the business model factor. The impulse responses are constructed as follows:

$$\frac{\partial \Delta y_{i,t+h}}{\partial Shock_t} = \hat{\Psi}^h + \hat{\Pi}^h BBM_{i,t} \quad (4)$$

Where $BBM_{i,t}$ corresponds with the *RETAIL* factor obtained through the factor analysis. From equation 4 it is clear that we have impulse response functions that vary at the bank level. We therefore calculate the average impulse response corresponding to the 25% highest *RETAIL* factor scores (retail banks), and the average impulse response corresponding to the 25% lowest *RETAIL* factor scores (non-retail banks).

tant monetary policy measures did not affect the balance sheet (e.g., OMT was pre-announced by the Draghi ‘whatever it takes’ speech in July 2012, operationally implemented in September 2012 but subsequently never activated). And finally, different conventional and unconventional policy measures were announced simultaneously (e.g. in January 2015, PSPP was announced joint with a decrease in the deposit facility rate and strengthened forward guidance) and were often largely anticipated. Based on the survey of econometric approaches used to identify monetary policy shocks in Rossi (2019), we opt for the SVAR because this approach allows us to incorporate a broad set of financial market indicators that should be linked to the decisions that banks make in terms of lending behavior, loan pricing and the riskiness of their loan portfolio. These strategic choices should be reflected in the accounting-based and the market-based variables we use to capture the banks’ risk and return profile (loan growth, loan risk, interest margin) as well as in their perceived profit potential (market-to-book value).

We estimate a time series of exogenous monetary policy shocks by modeling a set of relevant financial market variables in a structural VAR (SVAR) model at daily frequency as in Wright (2012) and Lamers et al. (2019):

$$Y_t = A_1 Y_{t-1} + \dots + A_p Y_{t-p} + R v_t \quad (5)$$

where Y_t is an N -dimensional vector of endogenous variables ($t = 1, \dots, T$), v_t an N -dimensional vector of orthogonal structural innovations with mean zero and A_1, \dots, A_p and R are $N \times N$ time-invariant parameter matrices. The reduced-form residuals corresponding to this structural model are given by the relationship $\varepsilon_t = R v_t$.

To estimate the SVAR we use a set of variables that capture the pass-through of monetary policy to the financial sector. Following Rogers et al. (2014), we select those variables that are expected to respond most to a monetary policy shock. More specifically, we include the 10-year German government bond yield, the 5-year forward inflation expectation based on inflation swap rates, an EU market index, the 5-year Spanish CDS spread and the VSTOXX index.⁶ Data are obtained through Thomson Reuters’ Datastream. The identification of policy shocks is based on the identification-

⁶The rationale for using the Spanish 5-year CDS spread is that Spain is the prototypical Euro Area periphery country which was hit by the banking crisis, a real estate crisis and by the sovereign crisis and it was not rescued with loans from the EFSF/ESM (compared to e.g. Portugal, Ireland or Greece). However, as a robustness check we also experimented with other sovereign stress indicators: the 5-year CDS spreads of Italy and France, an index of European 5-year sovereign CDS spreads and an index based on the 5-year CDS spreads of Spain, Portugal, Italy and Ireland. Our findings do not appear to be driven by the choice of the sovereign stress indicator.

through-heteroskedasticity strategy first proposed by Rigobon (2004), which assumes that the structural monetary policy shock is more volatile on monetary policy announcement days. The main idea is that there are days on which the volatility of the monetary policy shock is especially high, i.e. on days when there is a ECB announcement. Based on the differences in the volatility of the shocks during the two regimes, the structural VAR can uniquely be identified. In essence, we only assume that there is some kind of heteroskedastic pattern in the monetary policy shock while all other shocks are homoskedastic:

$$Var(v_t) = \Omega_t = \begin{cases} \Omega^{(0)} = \text{diag}(\omega_1, \omega_2, \dots, \omega_N) & \text{if no announcement} \\ \Omega^{(1)} = \text{diag}(\omega_1^*, \omega_2, \dots, \omega_N) & \text{if announcement} \end{cases} \quad (6)$$

It can be shown that, as long as the covariance matrix of the reduced form errors V_t changes on announcement days, these assumptions suffice to uniquely identify the first column of R and the structural monetary policy shock apart from their scale and sign. The model can be estimated following the iterative estimation procedure outlined in Lanne and Lütkepohl (2008).⁷ We normalize the monetary policy shock by fixing the response on impact of one of the included variables to a unit monetary policy shock. We define a unit expansionary monetary policy shock as a shock that decreases 5-year Spanish CDS spread with 5 percent. The set of days with monetary policy announcements is determined prior to the estimation of the SVAR model. This identification-through-heteroskedasticity approach is widely used in the literature to identify monetary policy shocks, for example Caporale et al. (2005), Gilchrist and Zakrajšek (2013), Rogers et al. (2014) and Arai (2017). We estimate a VAR of order 2 over a sample period from 1 October 2008 to 31 December 2018, i.e. the period during which the ECB implemented various types of conventional and unconventional monetary policy. The impulse responses are shown in figure 1.

[Figure 1 about here.]

We find that an expansionary monetary policy shock increases long-term inflation expectations and the value of the broad stock market index, while decreasing market-wide implied volatility ($VSTOXX$). Although the negative contemporaneous impact on the 5-year Spanish CDS is a consequence of our identification strategy, the effect remains significantly negative across the whole horizon. We do not observe a significant impact on the yield of the long-term safe asset, possibly

⁷For details on this estimation procedure we refer to Lamers et al. (2019)

due to a flight-to-safety effect in which monetary easing lowers the demand for safe assets, such as German bunds, by decreasing the risk of stressed sovereign bonds (see also Rogers et al., 2014, and Altavilla et al., 2016).

To capture the stance of monetary policy we could simply take the cumulative sum of the structural monetary policy shock over time. We would however ignore monetary policy shocks that occurred in the past which may still have an impact on the financial variables in the present time. In addition, as the average of the structural shock is zero by construction, the cumulative sum of the structural shocks will mechanically converge to zero at the end of the sample period. To avoid this, we perform a historical decomposition on the data as in Peersman and Smets (2003). Historical decompositions capture the accumulated effects of a structural shock on the VAR variables during a number of periods.⁸

[Figure 2 about here.]

We compute the contribution of the monetary policy shock to changes in the Spanish CDS spread in figure 2.⁹ We multiply the series with -1 so that we can interpret the monetary policy stance as accommodating when the series is positive which means that monetary policy decreased the Spanish 5-year CDS spread. More specifically, a sequence of positive monetary policy shocks indicates that monetary policy is becoming more expansionary and therefore the cumulative series reflects the monetary policy stance with respect to the prevailing economic environment and expectations of financial markets. As a consequence, a drop in the series can reflect a tightening of monetary policy but also the lack of monetary action or even that there were expansionary announcements that failed to live up to financial market expectations.

⁸Intuitively, a historical decomposition converts the time series Y_t as described in equation 5 in different components. In particular, the time series Y_t are linear functions of the history of structural shocks and an exogenous component which captures the initial conditions of the time series and the steady state. We can write the time series Y_t as follows:

$$Y_t = \underbrace{\sum_{j=0}^{t-(p+1)} A^j H C \varepsilon_{t-j}}_{\text{Contribution from shocks}} + \underbrace{A^{t-p} Y_p + \sum_{j=0}^{t-(p+1)} A^j H \mu}_{\text{Initial conditions and steady state}}$$

where

$$Y_t = \begin{bmatrix} y_t \\ \vdots \\ y_{t-p+1} \end{bmatrix}, A_t = \begin{bmatrix} A_{1,t} & \dots & A_{p,t} \\ I_{N(p-1)} & \dots & 0_{N(p-1) \times N} \end{bmatrix}, H = \begin{bmatrix} I_N \\ 0_{N(p-1) \times N} \end{bmatrix}$$

The historical decomposition provides an interpretation of historical fluctuations in the time series in terms of the identified structural shocks, in this case the monetary policy shock.

⁹The monetary policy stance obtained through the historical decomposition is not altered by the variable that is chosen to perform the decomposition.

The figure shows that the shocks are able to capture important monetary policy announcements, as well as the anticipation of some measures. In October 2008, the financial crisis hit the economy and monetary policy was perceived to be insufficient given market conditions. Additional monetary policy actions were introduced in the course of 2009, which reverted the monetary policy stance to expansionary. The one-year LTRO/CBPP1 announcement in May 2009 and the SMP announcement in May 2010 are among the largest expansionary daily shocks and can therefore be considered surprises to financial markets. In the following years, the monetary policy stance is perceived by financial markets as somewhat volatile, with periods of restrictive monetary regimes followed by expansionary shocks in the monetary policy stance, caused by events such as the ECB president Mario Draghi London speech in July 2012. The OMT announcement in September 2012 appears to have been largely anticipated following this speech in which he alluded to the implementation of additional unconventional monetary policy measures. The QE period which started in 2015 is sometimes perceived as a period of restrictive monetary policy, probably because of economic uncertainty stemming from the economic and political environment (e.g. Brexit). From 2017 onwards, the sustained monetary easing is considered by financial markets as effectively expansionary. An interesting example of the potential divide between policy intentions and market perception is described by Rostagno et al. (2019) in their account of the first 20 years of ECB monetary policy. In December 2015 the Governing Council decided to lower the deposit facility rate by 10 basis points. However, they conclude that the markets expected a larger reduction in the deposit facility rate, hence despite the intention of the ECB to be accommodating, the policy actions did not meet the expectations of financial markets (Rostagno et al., 2019). This resulted in a tightening of the monetary policy stance, as it is also captured in our figure 2, illustrating that our indicator of the monetary policy stance succeeds in identifying divergences between intended policy outcomes and actual market perceptions. This is an important value added of the identification approach since stock market perceptions determine our market-based measures of bank systemic risk (MES) and long-term profit potential (market-to-book).

We estimate the following model combining the estimated monetary policy stance and the macroprudential index:¹⁰

¹⁰We acknowledge that macroprudential policy and monetary policy do not move independently from each other. In the local projections setup we use, we are not able to take potential regime changes into account. The IRF's show the cumulative evolution in the bank risk and return profile variables after a shock at time 0 conditional on the policy stance at time 0.

$$\begin{aligned} \Delta y_{i,t+h} = & \alpha_i^h + \phi^h D_{j,t} + \Gamma^h CumMP_t + \Theta D_{j,t} \times CumMP_t \\ & + \sum_{k=0}^K \zeta_k^h Bank_{i,t} + \sum_{l=0}^L Y_l^h Macro_{i,t} + \varepsilon_{i,t+h} \end{aligned} \quad (7)$$

$\Delta y_{i,t+h}$ denotes the percentage change in the risk and return variables for bank i between time t and $t+h$. $D_{j,t}$ corresponds to the macroprudential tightening dummy in country j at time t . $CumMP_t$ is the cumulative monetary policy stance. α_i^h denote bank fixed effects. When we estimate the impact of macroprudential policy we also include time fixed effects and estimate the model with weighted least squares with weights defined by $w_{i,j,t} = \frac{D_{j,t}}{p_{j,t}} + \frac{1-D_{j,t}}{1-p_{j,t}}$. The differential effect of a macroprudential shock across different monetary policy regimes is then calculated using the partial derivative of the bank risk and return variables with respect to the macroprudential index.¹¹

4 Bank risk and return profile

To conduct our analysis we require accounting and market data for a sample of Eurozone banks. We obtain quarterly balance sheet and income statement data from SNL Financial which is available as of 2008Q1. We exclude financial holding companies that are not engaged in banking activity (e.g., asset management companies, online brokers or insurance companies). We exclude domestic subsidiary banks, but include foreign subsidiaries that satisfy the remaining criteria. Furthermore, we filter out banks that have a loans-to-assets ratio and a deposits-to-liabilities ratio lower than 20%. We use the accounting data to construct a set of bank business model variables to capture the asset, liability and income structure of the banks as in Mergaerts and Vander Venet (2016). We measure a bank's asset structure by defining variables that capture the composition of earning assets (the loan ratio, LTA). We use the ratio of customer deposits to total liabilities (DEP) and an unweighted capital ratio, i.e. the ratio of total equity to total assets (CAP), to capture banks' funding and capital structure. As an

¹¹More specifically, the impulse responses are constructed as follows:

$$\frac{\partial \Delta y_{i,t+h}}{\partial D_{j,t}} = \hat{\phi}^h + \hat{\Theta}^h CumMP_t \quad (8)$$

We calculate both the average impulse response of a macroprudential policy shock on the bank risk and return profile variables when monetary policy is in an accommodating phase ($CumMP_t$ is larger than 0) and the average impulse response of a macroprudential policy shock on the bank risk and return profile variables when monetary policy is tight ($CumMP_t$ is lower than 0).

indicator for the banks' income structure, we use the share of non-interest income in total income (DIV) as a proxy for revenue diversification. We also include bank size (SIZE), measured by total assets, as a control variable. Note that all variables have been winsorized at the 1% level. When quarterly data is lacking we linearly interpolate data points that are reported at a half yearly frequency to a quarterly frequency.¹² Income data reported at a quarterly frequency contains more variation than yearly data because of seasonality that is present in the data. To make sure the impulse responses are not influenced by this feature we calculate the income variables (such as the NIM and DIV) using a rolling window of the 4 previous quarters. Market data is obtained from Datastream.

To capture all dimensions of the bank's risk and return profile we construct 8 bank variables of which 6 are based on accounting data and 2 on market data. First, we calculate the bank's loan growth since the most common intermediate objective of macroprudential policy is bank credit growth. Second, we use loan loss provisions as a forward-looking measure of loan quality which is a reflection of a bank's assessment of the quality of its loans. Third, we measure individual bank distress probability using the Z-score, or rather its natural logarithm as the variable itself is strongly positively skewed. This variable is defined in the following way:

$$Z - score_{i,t} = \frac{\frac{total\ equity_{i,t}}{total\ assets_{i,t}} + E_{i,t}(ROA)}{\sigma_{i,t}(ROA)} = \frac{CAP_{i,t} + E_{i,t}(ROA)}{\sigma_{i,t}(ROA)} \quad (9)$$

We construct $E_{i,t}(ROA)$ and $\sigma_{i,t}(ROA)$ over a rolling window with three observations of ROA over the period t-2 to t. This procedure reduces the number of available observations slightly and removes banks with less than three consecutive observations. The Z-score should be interpreted as a distance-to-default measure, i.e. as the number of standard deviations ROA can diverge from its mean before the bank defaults. A higher Z-score indicates a safer bank. Fourth, We calculate the change in the bank's leverage ratio measured by total assets divided by total equity. Fifth, we investigate the impact of policy on the change in the ratio of risk-weighted assets to total assets which provides an (rough) indication of the riskiness of the loan portfolio of the bank. Sixth, we include a measure for bank profitability in the analysis, measured by the NIM. In addition to bank balance sheet characteristics, we also investigate the impact of macroprudential policies on 2 measures constructed using market data. First, we include a measure for bank systemic risk. A commonly used approach is to model systemic risk as the contribution of a bank to systemwide stress. One of the most frequently

¹²The general conclusions hold when we use the data that is not linearly interpolated.

used measures for systemic risk is the Marginal Expected Shortfall (MES) by Acharya et al. (2017) calculated as the expected loss of a bank's stock price conditional on a large shock to the financial system.¹³ Second, to capture the stock market's assessment concerning the franchise value of the bank we include the market-to-book ratio. Figure 3 displays the evolution of the bank risk and return profile variables over time. The graphs demonstrate the positive evolution of Eurozone bank risk during the sample period (lower loan loss provisions, lower leverage (i.e. higher capital ratios) and a higher Z-score). Most variables show the distress of the banks during the banking crisis and again during the sovereign crisis in de euro area.

[Figure 3 about here.]

The macro control variables described in section 3 (Methodology) that are used both in the first stage logit regressions and in the local projections are retrieved from the ECB Statistical Data Warehouse (SDW). We include the changes in bank credit to non-financial corporations to capture domestic credit growth in each country. Second, to control for developments in the real estate market we include the year-on-year change in the country- level residential property price index. Third, we include country-level GDP growth to account for economic activity. Fourth, we include the ratio of household debt to GDP in the model since policymakers use this measure as an indicator to initiate borrower-related macroprudential tools, such as loan-to-value ratios. To control for the level of volatility on the stock markets we include the VSTOXX, which is retrieved from Datastream. Last, we control for monetary policy and include the ECB MRO rate, which is also retrieved from Datastream.

The application of the sample selection criteria results in a dataset of accounting measures, depending on the risk or return profile variable that is used, for around 140 banks for a total of around 3400 bank-quarter observations at time $t=0$. The dataset using the market-based measures results in a sample of 63 and 64 Eurozone banks and around 2200 bank-quarter observations at time $t=0$ when using the MES or the market-to-book variable, respectively.

The descriptive statistics are given in table 2.

[Table 2 about here.]

¹³The MES measures a bank's expected equity loss when the market falls below a certain threshold over a given horizon and can be written as:

$$MES_{i,t} = E_{t-1}(r_{i,t} | r_{m,t} < C)$$

In line with Acharya et al. (2012) , the threshold C that defines a crisis is set at a -2% loss in the relevant market index over a one day period. As the market index we use the MSCI Europe. To estimate the different components of the MES we follow the procedure as described in Brownlees and Engle (2017) and Idier et al. (2014)

5 Empirical results

In this section we assess the impact of macroprudential and monetary policy on Eurozone banks' risk and return profile using accounting and market based measures of the banks' risk and return profile. Subsection 5.1 reports and discusses the results of the inverse propensity score regressions on bank risk and return profile measures in a local projections framework. We also check whether certain bank business models react more strongly to changes in the macroprudential policy stance. Subsection 5.2 investigates the impact of macroprudential policy across different monetary policy regimes.

5.1 The impact of macroprudential policy on the bank's risk and return profile

In order to investigate the impact of macroprudential policy on the bank risk and return profile variables, we apply the inverse propensity score procedure. We start by performing the first stage logit regression shown in equation 1. We run logit classification models for the tightening dummy $D_{i,t}$ since we want to account for macroeconomic variables that are supposed to be associated with the initiation of macroprudential policy actions. Hence, we include in this regression the year-on-year percentage change in GDP growth, the country-specific housing price index, the yearly growth rate of bank credit and household debt as well as country-fixed effects and year dummies. Table 3 presents the results of the first stage.

[Table 3 about here.]

Table 3 indicates that macroprudential tools are especially initiated after an increase in loan growth during the previous year. Also the VSTOXX appears to be a significant predictor for a tightening in the overall macroprudential policy stance. We report the AUC statistics which indicates the area under the receiver operating curve. The statistic measures the predictive ability of a model to correctly sort observations into "tightening" and "no tightening". The AUC takes on the value of 1 for perfect classification ability and 0.5 for an uninformed random classification. The AUC of the full model is 0.758 which indicates that the first stage is informative in predicting a tightening in the macroprudential stance.¹⁴

¹⁴We acknowledge that the first model specification, only including the lagged loan growth, has an even higher AUC statistic, indicating that this model specification is even better in predicting a macroprudential tightening in a certain country. In addition, specification 7 has less observations which could have an impact on the second stage results. We performed several robustness checks on the first stage regressions (different variables, different lag lengths and different time periods), and we find that the results are not sensitive to the specification that is chosen in the first stage. As a second

Having estimated the first stage logit model, we use the fitted probabilities from this model in the local projections setting as in Jorda (2005) estimated using weighted least squares as in Alam et al. (2019) and Richter et al. (2018). As discussed in section 3.1 the weights are defined by $w_{i,j,t} = \frac{D_{j,t}}{p_{j,t}} + \frac{1-D_{j,t}}{1-p_{j,t}}$, where we truncate $w_{i,j,t}$ at 10. Figure 4 shows the impulse response functions of a tightening shock in macroprudential policy on the bank risk and return profile variables. As explained in section 4 we construct 6 bank risk and return profile variables based on accounting data and 2 variables based on market data.

[Figure 4 about here.]

Figure 4 presents the impact on net loans (top left panel), 4 accounting-based risk and return profile variables (LLP ratio, RWA density, leverage and Z-score), one market-based systemic risk indicator (MES) and in the bottom row the two profitability variables, the banks' net interest margin (NIM) and the market-to-book ratio (for the subsample of listed banks). The first important result is that bank loan growth decreases following a macroprudential policy tightening, as intended by policymakers. Credit growth decreases with around 2 percentage points after 4 to 6 quarters following a tightening in macroprudential policy. This downward effect on bank lending is consistent with several papers focusing on aggregated indicators of bank lending, such as Cerutti et al. (2017), Akinci and Olmstead-Rumsey (2018), Lim et al. (2011), Kuttner and Shim (2016) and Poghosyan (2019) among others. The estimated impact of the results is in line with the existing literature where the impact varies between 0,3 percentage points the following quarter (Akinci and Olmstead-Rumsey, 2018) to 2,2 percentage points after 4 quarters (Cerutti et al., 2017) for the overall macroprudential index. In terms of bank risk and return profile, the evidence in figure 4 points to decreasing bank risk. We observe no significant change in the loan loss provision ratio, indicating that banks do not increase the riskiness of their loan portfolio. In addition, the contraction of lending is accompanied by a similar decline of the RWA density ratio, suggesting the absence of risk-shifting behavior: banks do not compensate the decline in the loan type(s) targeted by the macroprudential actions by investing in other riskier types of loans or by shifting exposures to riskier securities. It has to be noted that the post-2008 period is also characterized by the gradual implementation of Basel III and the compliance with

robustness check we investigate whether the first stage results are different when we also include the lagged cumulative macroprudential index as a covariate in the first stage regression. We find that the higher the macroprudential policy stance, the lower the probability of a new macroprudential initiation (mainly for liquidity and capital regulation). The results in the second stage remain unaltered, except for the market-to-book ratio, which decreases less following a macroprudential shock. This effect is mainly driven by capital and liquidity regulation for which the initiation depends on the stance of macroprudential policy in that specific country and which now receives a lower weight.

e.g. the LCR and the NSFR may induce banks to decrease their portfolio of risky long-term assets and shift to safer asset classes such as sovereign bonds, which would imply a decrease of the RWA density. This effect is documented by Banerjee and Mio (2018) who show that banks increase the share of high quality liquid assets while they reduce intra-financial loans as a response to liquidity regulation. Next to lower loan growth, we observe a decline in the leverage ratio, indicating that banks opt for deleveraging and holding more capital, which improves their risk profile. The leverage ratio decreases by around 3 percentage points after 2 years. Again, it has to be noted that this behavior may be driven by adherence to strengthened capital regulation in the Basel framework, which was implemented during the sample period. Combined, the improved bank risk profile metrics translate into a higher Z-score, indicating that the distance to default increases and hence bank resilience improves. Finally, we consider the MES as the market-based indicator of how stock market investors perceive the evolution of bank risk. Since the MES captures the probability of systemic stress for listed banks, the results indicate that market participants acknowledge the improved risk profile since the MES decreases significantly after 4 quarters. This finding corroborates the evidence in Meuleman and Vander Venet (2020) who report that announcements of various macroprudential policy tools exert a downward effect on the MES of European banks. The conclusion from figure 4 is that macroprudential policy in general is able to improve the risk profile of euro area banks, and hence that it is effective in supporting financial stability.

However, the positive effect of macroprudential policy on the bank's risk profile comes with a downside: current and longer-term bank profitability experience stress. We observe a negative effect on the NIM following a macroprudential shock. This result is significant in the short term and fades to marginally significant over the projection horizon, but it is apparent that the majority of the banks experience downward pressure on their margins. This is not unexpected since restrictions on lending or tightened liquidity rules typically result in lower interest income. Moreover, King (2013) shows that the introduction of liquidity rules such as the NSFR reduce bank net interest margins by requiring banks to use stable funding sources which have a higher funding cost. Additional insight comes from the way stock market investors assess the impact of macroprudential actions on the long-term profitability of the banks concerned. The market-to-book ratio exhibits a significant decline over the entire impact horizon, indicating that stock markets view macroprudential regulation as negative for bank market valuations. This result is in line with Richter et al. (2018) who find that stock market

prices are negatively affected by the introduction of loan-to-value ratios in 56 economies.

The overall conclusion from figure 4 is that while macroprudential regulation improves the risk profile of euro area banks, as intended, the constraints imposed by the new rules affect bank profits negatively, which may ultimately have an impact on the stability of the banking sector. We acknowledge that the results may potentially be influenced by cross-border banking flows that could lead to leakage effects and regulatory arbitrage (as found in Aiyar et al. (2014) and Reinhardt and Sowerbutts (2015)). We have however several reasons to believe that this bias will be rather small. In particular, we investigate the impact of a domestic macroprudential shock on a sample of domestic groups and foreign subsidiaries. First, foreign subsidiaries need to comply with regulation, which means that the impact of a macroprudential shock will be visible at the foreign subsidiary level, regardless of regulatory arbitrage or leakage effects. If there are indeed leakage effects, this can undermine the effectiveness of the macroprudential measure to curb credit growth at the country level. The incentives for regulatory arbitrage are stronger for institution-based measures as they target the bank rather than the borrowers. This calls for an automatic and compulsory reciprocity agreement for institution-based measures. There is less incentive for regulatory arbitrage with respect to borrower-based regulation as the regulation is linked to the borrower. Second, for domestic groups at the consolidated level, the impact of macroprudential measures may be less visible as there can be a shift of activities to foreign subsidiaries. We perform a robustness check whereby we include the domestic subsidiary rather than the domestic group because the impact will be directly measurable at the domestic subsidiary level. We find however that the difference in the results is negligible.¹⁵

In a next stage, we analyze how macroprudential policy is transmitted across different bank business models. We hypothesize that different types of macroprudential measures will affect different types of banks in a heterogeneous way. When, e.g., the macroprudential authority undertakes actions to limit certain exposures, only banks with such exposures will need to take remedial action. We examine this hypothesis by interacting the macroprudential index with the *RETAIL*-factor we obtained after running a factor analysis on a set of bank business model variables (see section 3.1). This *RETAIL*-factor captures the *retailness* of the banks since it positively loads on the loan, deposit and capital ratios, but is negatively related to size and income diversification. Figure 5 shows the results of the local projections setting where we interact the macroprudential shock with the *RETAIL*-factor from the factor analysis.

¹⁵The results of this test are available upon request.

[Figure 5 about here.]

The impulse responses show that the impact of macroprudential tightenings is more pronounced for retail-oriented banks compared to their non-retail counterparts. For example, credit growth decreases with around 3 percentage points after 4 quarters for a retail-oriented banks, while for a non-retail bank the impact is limited to less than 1 percentage point. The decrease in profitability, measured by both the NIM and the market-to-book that was found in figure 4 is mainly attributable to retail banks which seemingly suffer more from macroprudential policy actions. The negative impact on the profitability in turn negatively influences the Z-score of retail banks. In contrast, the Z-score of non-retail banks slightly increases following a macroprudential policy shock. In summary, retail-oriented banks are more sensitive to macroprudential policy shocks compared to other banks, probably because they have more difficulties to absorb the shock since they are more dependent on mortgage loans, which are frequently targeted by macroprudential regulators. In contrast, non-retail banks have a more diversified asset and revenue portfolio which make them less sensitive to changes in prudential regulations. The results are in line with the findings of Altunbas et al. (2018) who find that smaller banks react more strongly to macroprudential changes. Meuleman and Vander Venet (2020) find that the individual risk component, which is a subcomponent of the MES capturing idiosyncratic bank risk, decreases more strongly for retail-oriented banks. An implication of these results is that retail banks should diversify their asset portfolio in order to make them less sensitive to changes in macroprudential policy.

5.2 The interactions between macroprudential policy and monetary policy

The crucial research question for policymakers is whether or not the transmission of macroprudential policy varies across different states of monetary policy. To check whether or not this is the case, we first interact the macroprudential shock with the stance of monetary policy, constructed as described in section 3.2. Figure 6 shows the impulse responses of the local projections of a tightening in macroprudential policy and its effectiveness across monetary policy regimes. The red lines correspond with the response of a tightening in macroprudential policy when monetary policy is restrictive, i.e. when the monetary policy stance is below 0. The green lines indicate the impulse responses of a macroprudential tightening on the bank risk and return profile variables when monetary policy is considered to be loose by market participants, i.e. when the monetary policy stance is positive.

[Figure 6 about here.]

Figure 6 shows the estimation results over a projection horizon of 8 quarters. We first interpret the impulse responses for the situation in which tightening macroprudential measures are announced in a period characterized by a restrictive monetary policy stance (depicted by the solid red line). In this case, the two policies reinforce each other in lowering credit growth, as intended by both the monetary and the macroprudential authorities. In terms of bank risk, the behavior of the bank risk profile variables is consistent with improved bank stability. We not only find that net lending decreases but there is also no evidence of risk-shifting behavior, since the RWA density decreases and the LLP ratio remains constant or even decreases slightly. Simultaneously, the leverage ratio decreases significantly (banks become better capitalized) and the increasing Z-score, as an overall measure of bank health, signals improving bank resilience. For policymakers, this is the desired outcome of their actions since macroprudential policy and restrictive monetary policy work in the same direction. These findings are in line with Gambacorta and Murcia (2019) and David et al. (2019) who also document that macroprudential and monetary policy push in the same direction, i.e. they restrain credit growth. This result is also confirmed by Popoyan et al. (2017) who find that monetary policy and macroprudential regulation are complementary in increasing the resilience of the banking sector. However, improved stability comes at a price, since we find evidence of pressure on current and future profitability. On average, the impulse response for the NIM is not significant, but the market-to-book ratio declines significantly over the projection horizon, indicating that macroprudential measures combined with restrictive monetary policy effectively impose constraints on banks. These negative consequences on the banks' franchise value are (almost) identical to the effects exhibited in figure 4 (the standalone effect of tightening macroprudential actions) and from figure 5 we know that these negative effects on bank profitability are particularly pronounced for retail banks. Hence, when macroprudential policy and monetary policy operate jointly in a restrictive regime, the risk profile of Eurozone banks improves, but at a cost of lower anticipated profitability.

An interesting case is when there is a potential trade-off between monetary and macroprudential policy. This is the prevailing environment in the post-2008 era, since it is characterized by the simultaneous introduction of restrictive macroprudential measures following the financial and sovereign crises in Europe as well as unprecedented conventional and unconventional monetary policy by the central bank. However, as our SVAR in figure 2 demonstrates, monetary policy actions intended by

the ECB as stimulating were not always perceived as such by financial markets. Hence, our impulse responses to bank risk and return variables should capture those cases in which macroprudential measures were introduced in periods in which the monetary actions of the ECB are considered by markets as unambiguously accommodating. In figure 6, the solid green line captures the impact on the banks' risk and return profile of macroprudential measures in periods of perceived monetary stimulus. The top left panel shows that bank loan growth does not slow down initially and even increases significantly after 4 quarters, suggesting that the transmission of macroprudential policy is affected by the presence of loose monetary policy. For the central bank, this is the most desired outcome since its actions are geared towards stimulating lending to the real economy. This result confirms the common finding that ECB monetary policy succeeded in decreasing loan rates and increasing bank lending (see Rostagno et al., 2019). The main concern of policymakers is that more lending may be accompanied by increased risk taking by banks, by engaging in lending to riskier borrowers or shifting towards riskier securities (Heider et al., 2019). Our results are not compatible with this risk-taking channel. Our impulse responses show that loan loss provisions do not increase and the RWA density even decreases significantly, suggesting the absence of risk-shifting behavior. At the same time, the capital adequacy of the banks increases significantly (lower leverage) and the same observation holds for the Z-score. Our market-based risk indicator (MES) never increases over the projection horizon. The conclusion is that accommodating monetary policy may entail incentives for banks to take more risk, but in the period under investigation, our results indicate that macroprudential measures were sufficiently strong to deter banks from excessive risk taking. This conclusion is consistent with the findings in Albertazzi et al. (2020) who examine the pricing behavior of Euro Area banks and conclude that any additional risk taken in the post-2014 period was not inadequately priced. Similar evidence is reported for the rebalancing of bank securities portfolios. Albertazzi et al. (2020) report that, since the start of the APP, banks' bond portfolios have shifted through an active rebalancing out of the safest categories of securities into other investment grade bonds. However, they argue that over the same period, this effect was more than offset by positive rating migration caused by improved macroeconomic conditions. Moreover, they show that banks' portfolio rebalancing has not translated into a loading up of domestic sovereign debt securities, not even in those economies where such securities offer higher yields. Our findings are also corroborated by Soenen and Vander Vennet (2020) who investigate the impact of ECB monetary policy on bank CDS spreads and conclude that over the

post-2008 period, accommodating monetary policy by the ECB is associated with a beneficial impact on the market-perceived default risk of European banks.

Macroprudential measures announced in an environment of accommodating monetary conditions are associated with higher loan growth, but do not induce excessive risk taking by banks. The consequences of this policy mix on bank profitability is, however, less benign. We observe in figure 6 that the impact on the NIM is negative, although statistically not significant. According to ECB (2020) banks have increased their loan volumes in an effort to protect their interest margin, but such compensation is finite. More importantly, we observe a marked deterioration of the banks' market-to-book value as a reflection of the investors' conviction that low for long interest rates ultimately compress bank interest margins and put their profitability and franchise value under stress. Altavilla et al. (2018) argue that the ECB's APP and negative deposit facility rates have a close to zero net effect on banks' ROA since positive effects (capital gains on securities and better credit quality) compensate any decline in the banks' net interest margins. However, while capital gains and lower loan losses are temporary, the gradual decline of net interest margins is a persistent phenomenon as long as monetary policy remains ultraloose. The decline in market-to-book ratios in the regime of accommodating monetary policy is significantly more pronounced than under a restrictive stance. Our results are consistent with Borio et al. (2017) and Claessens et al. (2018) who examine the impact of low policy rates on bank interest margins and conclude that long periods of low rates indeed compress bank margins. Hence, from the bottom panel of Table 6, we conclude that the combination of restrictive macroprudential policies and prolonged monetary accommodation may turn out to be detrimental for bank health and, ultimately, financial stability.

6 Extensions and robustness checks

In this section we perform several extensions and robustness checks to validate the results on the interaction between monetary policy and macroprudential policy. More specifically, we construct a more granular macroprudential policy index where we subdivide the index in different subindices based on their macroprudential objective in subsection 6.1, an alternative (conventional) monetary policy stance using country-specific Taylor rules in subsection 6.2, and an alternative unconventional monetary policy stance using the identification through external instruments approach in subsection 6.3.

6.1 A more granular macroprudential index based on the macroprudential objective

In the baseline regression results we use the aggregate macroprudential policy index, including all policy actions. As different macroprudential policy tools have different objectives, it may be insightful to investigate whether different kinds of macroprudential policy tools have different effects on the bank risk and return variables and whether the effectiveness of the different tools varies over monetary policy regimes. For this setup, we regroup the tools in 3 types of categories according to their objective and we distinguish (1) credit growth restrictions which incorporate loan-to-value ratios, loan-to-income ratios, debt-serv-to-income ratios, maturity and amortization restrictions and risk weights on mortgage loans and commercial loans, (2) liquidity regulations covering liquidity coverage ratios, net stable funding ratios, loan-to-deposit ratios, and other liquidity requirements and (3) measures that impact the resilience of the banking sector such as minimum capital requirements (mainly the regulations under the CRR/CRD framework), capital buffers (systemic risk buffers, countercyclical buffers, capital conservation buffers), taxes on financial institutions and loan loss provisioning rules.

We first apply the inverse propensity score procedure on the 3 disaggregated macroprudential indices to estimate the response of bank risk variables to a macroprudential shock. We start by performing the first stage logit regression described in equation 1. Table 4 presents the results of the first stage.

[Table 4 about here.]

From table 4 we can see that macroprudential tools are initiated after an increase in the loan growth during the previous year. The effect is most pronounced for the credit growth tools, as expected. The *VSTOXX* appears to be a predictor for both the liquidity tools and the resilience measures.

[Figure 7 about here.]

Figure 7 shows the impulse responses for a shock in the different macroprudential subindices. When we first focus on loan growth, we see that all three macroprudential policies decrease credit growth. While the effects of liquidity measures and resilience measures only become visible after several quarters, credit risk measures impact the bank risk variables immediately. From the MaPPED database we know that the time period between the announcement of credit growth tools and the

actual enforcement is on average 2.5 months while the phase-in period is on average 3.3 months, 7.6 months and 4.8 months for liquidity regulation, minimum capital requirements and capital buffers, respectively. Banks thus need to adjust faster to credit risk measures compared to other measures. The impact of credit risk measures is also somewhat higher than that of resilience and liquidity measures: the initiation of a credit risk measures, such as a loan-to-value ratios, decrease bank loan growth with 3.12 percentage points after 2 years, while liquidity and resilience measures decrease lending of banks with respectively 1.99 and 1.21 percentage points, on average. This result is in line with Kuttner and Shim (2016) who find that targeted credit policies such as debt-service-to-income requirements and housing-related taxes can be used as tools to restrain housing credit growth. In contrast, supply-side credit policies such as risk weights and provisioning requirements had no significant impact on housing credit. The estimated impact of credit growth measures on credit growth is in line with the existing literature where the estimates range between 2,6 percentage points per year (Zhang and Zoli, 2016) and 4 to 7 percentage points per year (Kuttner and Shim, 2016). With respect to loan loss provisions, we find that the implementation of liquidity regulation significantly decreases the loan loss provisions in the longer run. Turning to the risk profile of the loan portfolio, as measured by the risk weighted assets to total assets we observe that both liquidity measures and resilience measures induce banks to hold a safer asset portfolio. However, for the credit risk measures we see the opposite as banks increase the amount of risky assets in the total asset portfolio. These results are compatible with a risk-shifting explanation. Since lending-oriented tools force banks to lower their exposures to certain types of counterparties or to disinvest certain types of loans or securities, the banks may shift the asset composition towards exposures that make them more interconnected to the financial system. As a typical example, restrictions on mortgage lending, e.g. in the form of loan-to-value caps or higher capital weights, may induce a shift to corporate lending or securities, which exposes these banks to business cycle shocks. This finding is in line with Acharya et al. (2018) who find that banks increase their holdings of risky securities and corporate credit in response to the introduction of loan-to-value or loan-to-income limits in Ireland. Cizel et al. (2016) also show that mainly quantity restrictions, such as exposure limits, are more prone to cause strong substitution effects. In terms of policy this calls for a careful calibration of macroprudential measures in order to avoid the unintended consequences of risk-shifting behavior by the affected banks. Auer and Ongena (2019) also find evidence of a risk-shifting channel following macroprudential tightenings as banks

shift their lending to more commercial lending and to smaller and riskier firms using a loan-level dataset of credit granting in Switzerland .

When we focus on the leverage ratio we find that liquidity regulation decreases the leverage ratio after 1 year, which is a result of the decrease in loan growth. The leverage ratio for credit risk measures decreases more rapidly, since credit growth reacts immediately after the announcement of these tools. Surprisingly, for the resilience measures, which consist mainly of minimum capital requirements and capital buffers, the effect on the leverage ratio is limited. This may be due to the fact that the announcement of capital buffers comes on top of already enforced capital regulation (Basel 3). Since most banks hold capital buffers in excess of the regulatory minimum, the announcement of additional capital buffers may not impose additional constraints. Another explanation is that capital regulation mainly targets the weighted capital ratio, while the leverage ratio is an unweighted measure for bank capitalization. In response to capital related measures bank react with a decrease in the risk weights of the assets, rather than with a deleveraging. This is also found by Cappelletti et al. (2019) who find that banks react to O-SII capital buffers by adjusting the risk-weighted assets rather than by reducing credit supply. With respect to the Z-score, we only find that liquidity regulation widens the distance to default after 1 year. For the MES, the results are less clear. The MES is a quite volatile measure, however, for the resilience measures we can see that the MES has a tendency to decrease after 1 year, indicating that these measures are indeed able to increase financial stability. Finally, we investigate the impact of the different macroprudential measures on the profitability indicators. For the NIM, we find that the impact is rather limited and mainly insignificant for all three measures. The negative impact on the NIM is most pronounced for the resilience measures. In contrast, the market-to-book value decreases considerably following macroprudential regulation and this effect is visible for all three macroprudential tools. The effect is most pronounced for the liquidity tools: on average, the introduction of liquidity regulation decreases the market-to-book value with around 30 percentage points, and the effect is quite persistent.

In a next stage, we again interact the macroprudential policy tools with the monetary policy stance as calculated in section 3.2. Figure 8 shows the results.

[Figure 8 about here.]

From the impulse responses we can see that the effects over the monetary regimes are similar in most of the cases. However, several results stand out. First, with respect to loan growth, liquidity tools

and resilience measures appear more effective during periods of tight monetary policy. Second, when we consider risk weighted assets to total assets, we observe that banks reduce the riskiness of the asset portfolio both in loose and tight monetary regimes, following liquidity and resilience measures. However, the risk-shifting behavior, where banks shift to riskier assets in response to credit growth measures, is only present when monetary policy is tight. This is in line with the results of Becker and Ivashina (2014) who find that banks substitute loans with bonds when both lending standards and monetary policy are tight. Parallel to this result, also the Z-score falls following the credit growth measures, but only when monetary policy is tight. This result indicates that retail banks may become more vulnerable to business cycle shocks. A final noteworthy result is that the resilience measures appear more effective in decreasing the MES when monetary policy is tight.

6.2 An alternative measure for the monetary policy stance: Taylor rule

Using a VAR approach to estimate monetary policy shocks allows us to capture current and anticipated monetary policy changes. An alternative measure to capture the monetary stance is the use of a Taylor rule which indicates the optimal policy rate given deviations in inflation and output compared with their target levels. However, as we are interested in the monetary policy stance in the Eurozone in the post-2008 period, we cannot use the policy rate because of the zero lower bound constraint. Therefore, we estimate a Taylor rule on the deposit facility rate which is not limited by the zero lower bound. To construct counterfactual interest rate path we use the specification proposed by Clarida et al. (1998), in which the target interest rate responds to deviations in inflation and output from their targets. We also incorporate an interest rate smoothing mechanism, in order to model the partial adjustment undertaken by central banks. We estimate the following model:

$$i_{i,t} = \rho i_{i,t-1} + (1 - \rho)\alpha + \beta(\pi_{i,t} - \pi^*_{i,t}) + \lambda(y_{i,t} - y^*_{i,t}) + \varepsilon_{i,t} \quad (10)$$

with $i_{i,t}$ the deposit facility rate, $\pi_{i,t} - \pi^*_{i,t}$ the difference between the inflation rate and the target inflation in country i at time t and $y_{i,t} - y^*_{i,t}$ the output gap of country i at time t . We estimate a country-specific Taylor rule to account for different macroeconomic conditions in different Eurozone member countries. As Nechio (2011) points out, a single policy rate is suboptimal as the economic circumstances differ between countries, especially between core and peripheral countries.¹⁶

¹⁶The peripheral countries in this exercise are Italy, Spain, Ireland, Greece and Cyprus. The core countries represent

The inflation rate corresponds to the OECD's annual growth rate of the Consumer Price Index. The output series corresponds to the Eurostat's Quarterly National Accounts' GDP data, in millions of 2010 Euro, seasonally adjusted. The output gap was obtained using a Hodrick-Prescott filter on the logarithm-transformed output series, multiplied by 100. After estimating equation 10 we forecast the counterfactual interest rate paths. The results are presented in figure 9, along with the observed deposit facility rate for the post-2008 period. We show the average Taylor rule for periphery and core countries.

[Figure 9 about here.]

[Figure 10 about here.]

We again interact the macroprudential policy shock with the monetary policy stance, as estimated by the Taylor rule. Figure 10 shows the impulse response functions. Looking at the impulse responses of credit growth, we again find that macroprudential policy appears to be somewhat more effective during periods of tight conventional monetary policy. In addition, the impact on the MES is also somewhat more negative during tight monetary stances. The negative impact of macroprudential policy on the bank profitability measures is more notable during times of loose monetary policy: the NIM decreases more during periods of loose monetary policy compared to periods of tight monetary policy. This result is comparable to the case where we interact the macroprudential policy shock with the VAR-based monetary policy stance, however the differential effects are less significant.

6.3 An alternative measure for the monetary policy stance: identification using external instruments

An alternative way to identify monetary policy shocks is to use external sources of information, that is, external instruments. These external instruments can be thought of as noisy observations of, in this case, the monetary policy shock but which are not correlated with other shocks. The instruments are thus not necessarily identical to the true monetary policy shock, as they might contain some measurement error, but, as long as they are uncorrelated with the other shocks in the system, they can be used to identify monetary policy (Rossi, 2019). However, they need to be exogenous. We again start with a simple structural VAR model. The VAR model can be summarized as follows:

all other Eurozone countries.

$$Y_t = \Pi(L)Y_{t-1} + \mu_t \quad (11)$$

The reduced form shocks and the structural shocks are linked to one another by some matrix B :

$$\mu_t = B\varepsilon_t \quad (12)$$

We use the identification strategy of Gertler and Karadi (2015), Stock and Watson (2012) and Mertens and Ravn (2013). If we find an instrument Z for the shock of interest we can identify the first column of B , and thus the impulse response functions of the system, without imposing zero (or other) restrictions. The following conditions need to be satisfied:

$$E(\varepsilon_{mp,t}, Z_t) = \phi \quad (\text{relevant instrument}) \quad (13)$$

$$E(\varepsilon_{other,t}, Z_t) = 0 \quad (\text{exogeneity}) \quad (14)$$

We denote the structural monetary policy shock as $\varepsilon_{mp,t}$ and all other shocks as $\varepsilon_{other,t}$. The instrumental variable captures the exogenous component of the monetary policy shock. For more details and implementation, we refer to Gertler and Karadi (2015), Stock and Watson (2012) and Mertens and Ravn (2013). The VAR is estimated with the same 5 variables as the ones used in section 3.2: the 5-year Spanish CDS spread, the 10 year German government bond yield, the 5-year forward inflation expectation based on inflation swap rates, an EU market index, and the VSTOXX index. The model is estimated from 2008Q4 until 2018Q4 at a daily frequency. In this case, we assume that monetary policy shocks impact the 5-year Spanish CDS spread.

As an instrument for unconventional monetary policy we use the monetary policy surprises as constructed by Altavilla et al. (2019). In this paper, the authors construct the "Euro Area Monetary Policy Event-Study Database (EA-MPD)".¹⁷ The database contains tick data on a number of asset prices over relevant ECB policy windows that capture two different steps in the communication of the ECB. First, at 13.45 Central European Time (CET) a brief press release that only contains the decision on policy rates is published, while announcements of non-standard measures are mainly made as of

¹⁷The database is updated periodically and is available at https://www.ecb.europa.eu/pub/pdf/annex/Dataset_EA-MPD.xlsx

14.30 CET during a press conference and a Q&A session during which the ECB President reads a prepared text, the Introductory Statement (IS), on the rationale behind the decision. The database contains the change in a number of asset prices covering both the press release and press conference windows.¹⁸ In particular, the EA-MPD provides information on the full OIS yield curve, ranging from 1 week to 20 years maturity, German, French, Italian and Spanish government bond yields, the Eurostoxx and several exchange rates. As we want to capture exogenous changes in unconventional monetary policy we use the change in the Spanish 10-year government bond rate around ECB press conferences. This variable is presumably highly correlated with the 5-year Spanish CDS spread which makes it an optimal external instrument. We complement the database with 3 additional important central bank events which are non-meeting days: May 10th, 2010 (Securities Market Programme (SMP)), August 8th, 2011 (Reactivation of SMP) and July 26th, 2012 (Draghi's London speech: OMT).¹⁹ The explanatory power of the instrument can then be examined by regressing the reduced form VAR residuals of the monetary policy equation on a constant and the external instrument. The first-stage F-statistic of the instrument turns out to be 66.8 which is highly above the Stock et al. (2002) threshold of an F-statistic of 10 for having possible weak instrument problems. We are therefore confident about our choice of an accurate instrument.

The monetary policy shock we finally extract from the VAR has a correlation of 82.6% with the monetary policy shock identified when using the 'identification-through-heteroskedasticity' approach of Rigobon (2004). We again define a unit expansionary monetary policy shock as a shock that decreases the Spanish 5-year CDS spread by 5 percent upon impact. The impulse responses are shown in figure 11.

[Figure 11 about here.]

In line with the impulse responses obtained through identification based on heteroskedasticity of the structural shocks (Rigobon, 2004) we find that an expansionary monetary policy shock increases long-term inflation expectations at impact as well as the value of the market index, while market-wide implied volatility (*VSTOXX*) decreases. In contrast to the identification-through-heteroskedasticity impulse responses we find that the German 10-year government bond yield slightly decreases at time 0, which indicates that policy actions that impact the long-run safe yields, such as QE, receive a higher

¹⁸More specifically, the press conference window is described as the change in the median quote from the window 14:15-14:25 before the press conference to the median quote in the window 15:40-15:50 after it.

¹⁹For these days we use the daily change in the Spanish 10-year government bond yield.

weight when estimating monetary policy through the 'identification through external instruments' approach.

After having estimated the alternative monetary policy stance we transform the series to a quarterly frequency by taking the average of the series over the corresponding quarter. To convert the monetary policy shock to a monetary policy *stance* we again calculate the contribution of the monetary policy shock to changes in the Spanish 5-year CDS spread. We then interact this monetary policy stance with the macroprudential shock in order to evaluate the effectiveness of macroprudential policy across different monetary policy regimes. The results are given in figure 12.

[Figure 12 about here.]

We again find that macroprudential policy appears to be more effective during periods of tight conventional monetary policy. The effect is most pronounced for bank loan growth. In addition, the impact on the MES is also negative during tight monetary stances. The negative impact of macroprudential policy on the bank profitability measures is more notable during times of loose monetary policy: the market-to-book value decreases more during periods of loose monetary policy compared to periods of tight monetary policy. These results are comparable to those we find when we interact the macroprudential policy shock with the VAR-based monetary policy stance. Hence, our findings are robust to alternative identifications of the monetary policy stance.

7 Conclusion

Macroprudential policy is in vogue. Since the global financial crisis, macroprudential policies have gained prominence worldwide as a tool to maintain financial stability. In the Euro Area, the institutional framework has been adapted through the implementation of the Banking Union and the designation of macroprudential authorities in the member states. Borrower-related measures, such as LTV caps, and lender-related instruments, such as countercyclical capital buffers, have been introduced in several countries in order to deal with financial risks in the banking sector. Since both monetary policy and macroprudential policy may affect risk behavior by banks, it is important to establish whether or not the effectiveness of macroprudential policy varies across different monetary policy stances.

We tackle this important policy question empirically by analyzing the impact of macroprudential policy on the risk and return profile of Euro Area banks and by examining the interaction between

monetary and macroprudential policy over the 2008-2018 period. Our sample consists of 140/64 Euro Area banks for which we consider a coherent set of accounting-based (140 banks) and market-based (64 banks) indicators of the banks' risk and profit profile. For the identification of macroprudential policy, we apply an inverse propensity score weighting estimation in order to avoid endogeneity issues. The monetary policy stance is captured by a structural VAR in order to account for current and anticipated macroeconomic and financial market conditions. We use the local projections approach to assess the impact of macroprudential policy, and their interaction, on bank risk and return profiles over a 2-year impact horizon.

The main findings can be summarized as follows. First, considered in isolation, we confirm that macroprudential policy is effective in restraining bank risk, as intended by the macroprudential authorities. Tightening macroprudential measures are typically associated with less lending and lower bank asset risk and these features translate into lower overall bank risk, both accounting-based (Z-score increases) and market-based (MES decreases). However, the downside is that the announcement of macroprudential tools is accompanied by lower bank profitability over the projection horizon, leading to a significant decrease in the market-to-book ratio, reflecting the market perception that imposing constraints on banks causes stressed current and future bank profitability. When considering the banks' business model, we find that for both lending and profitability the effects are more pronounced for retail banks compared to their non-retail counterparts. This is not unexpected since the banks with a retail profile are most active in traditional lending, which is the focus of macroprudential measures targeting credit growth. Nevertheless, the negative consequences for the net interest margin and the market-to-book ratio are also more pronounced for retail-oriented banks, which may affect their future viability. This conclusion indicates that regulatory authorities should mind the business model of banks when imposing constraints.

Finally, we assess whether the effectiveness of macroprudential measures varies conditional on the stance of monetary policy. We find that when tightening macroprudential measures are announced in a period characterized by a restrictive monetary policy stance, the two policies reinforce each other in lowering credit growth, as intended by both the monetary and the macroprudential authorities. Moreover, in terms of bank risk, the behavior of the bank risk profile variables is consistent with improved bank stability. From a policy perspective, the most interesting case is when there is a potential trade-off between monetary and macroprudential policy, because the prevailing environment

in the post-2008 era is characterized by the simultaneous introduction of restrictive macroprudential measures following the financial and sovereign crises in Europe as well as unprecedented conventional and unconventional monetary policies by the central bank. In this case, we document that loan growth increases, suggesting that the transmission of macroprudential policy to credit growth is affected by the presence of loose monetary policy. For the central bank, this is the intended outcome since its actions are geared towards stimulating lending to the real economy. Interestingly, while accommodating monetary policy may entail incentives for banks to take more risk, our results indicate that macroprudential measures were sufficiently strong to deter banks from excessive risk taking. In other words, macroprudential policy succeeds in maintaining bank stability also in periods of monetary accommodation. Yet, there is an important downside: we observe a marked deterioration of the banks' market-to-book value as a reflection of the investors' conviction that low for long interest rates ultimately compress bank interest margins and put their profitability and franchise value under stress. Our conclusion is that the combination of restrictive macroprudential policies and prolonged monetary accommodation may turn out to be detrimental for bank health and, ultimately, financial stability.

Our main findings are corroborated when we estimate the monetary policy stance with a Taylor rule or when we use the 'identification-through-external-instruments' approach. When we consider the impact of specific macroprudential policy tools, we find that credit growth measures, such as loan-to-value ratios, have an immediate and stronger negative impact on loan growth compared to liquidity regulation or measures aimed at the resilience of banks, such as capital regulation. However, we also find evidence for risk-shifting behavior by banks confronted with targeted credit measures: banks increase the riskiness of the loan portfolio in response to credit constraints. In trying to comply with the rules, these banks may engage in riskier activities by, e.g., shift to more risky corporate lending or securities.

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Figures

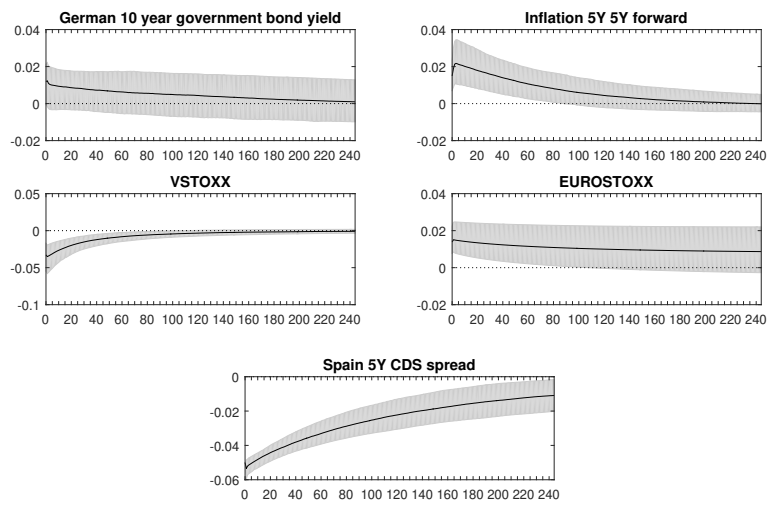


Figure 1: Impulse response function of the variables to a unit monetary policy shock. Gray areas represent 68% confidence intervals that are obtained through a stationary bootstrap with expected block length 10 for non-announcement days. Announcement day residuals are bootstrapped separately. The horizontal axis represents the horizon of the impulse response function in working days, i.e. the IRF's are plotted for a horizon of 240 days.

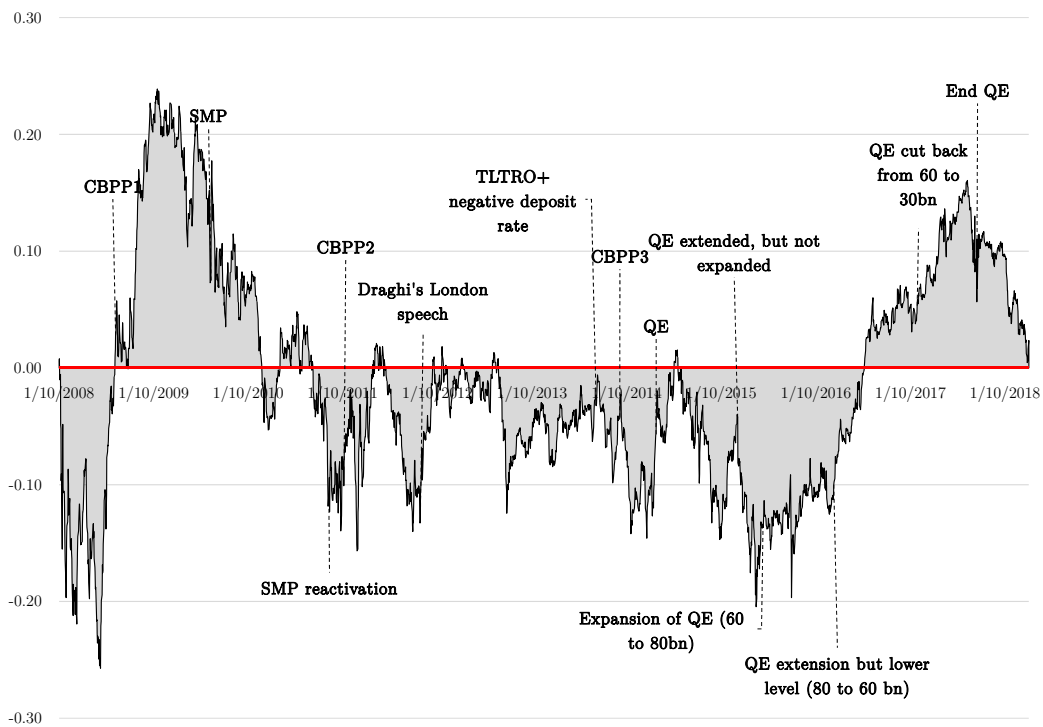


Figure 2: This graph shows the cumulative monetary policy shock series. The monetary policy shock is estimated using an identification-through-heteroskedasticity approach first proposed by Rigobon (2004). A sequence of positive monetary policy shocks indicates that monetary policy is becoming more expansionary, a drop in the series can reflect a tightening of monetary policy but also the lack of monetary actions.

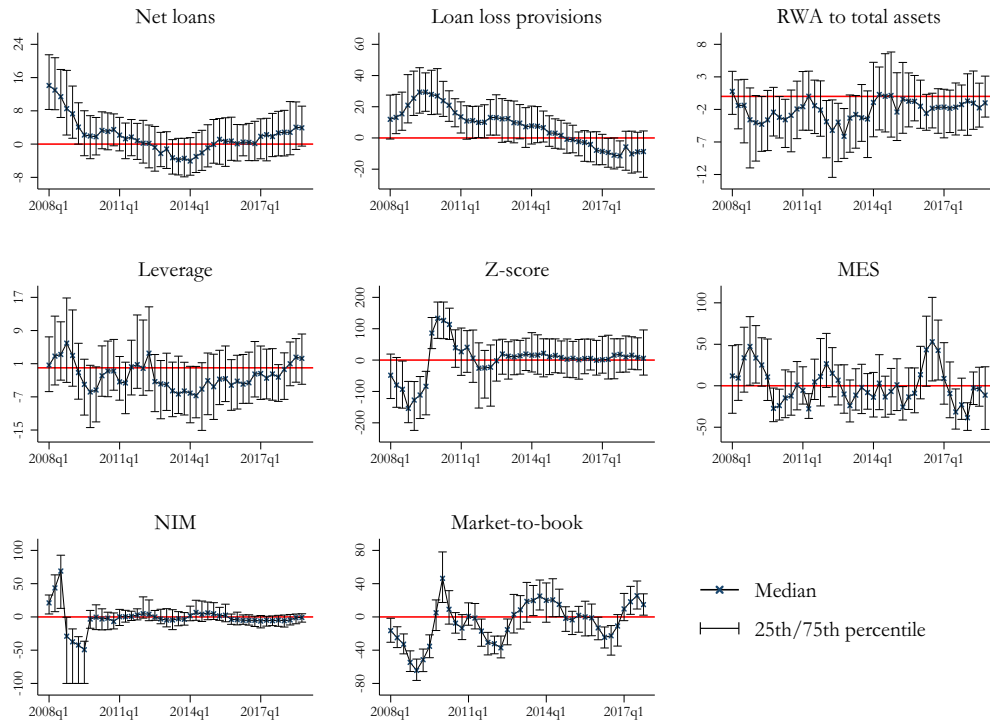


Figure 3: Evolution of the growth of the bank risk and return profile indicators for European banks. The black dashed indicates the median. The dark area represents the 25th and 75th percentiles.

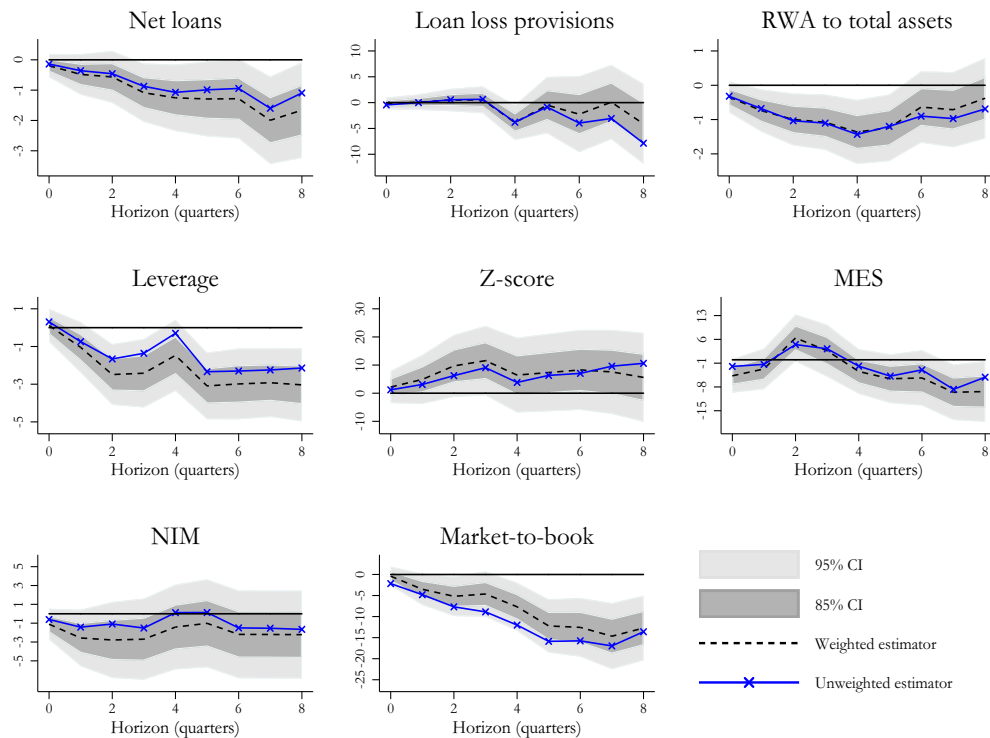


Figure 4: Baseline results of a tightening shock in macroprudential policy on a set of bank risk and return profile variables. The response is expressed in percentage point changes. To estimate the responses we estimate a local projections model with weighted least squares, where the weights are defined by an inverse propensity score model, as described in section 3.1. The black dashed line represents the coefficients of this weighted estimator. The blue solid (crossed) line indicates the coefficients of the unweighted estimator. The index that is used is the overall macroprudential index covering all policy tools. The dark area represents the 95% confidence intervals. The lighter area indicates the 85% confidence intervals. The horizon is measured in quarters.

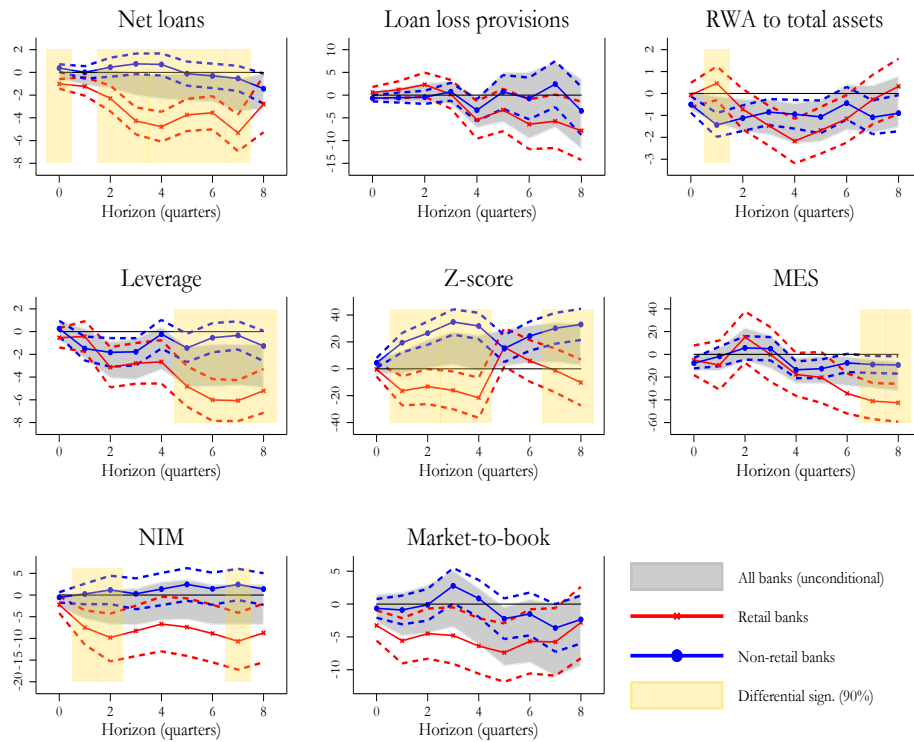


Figure 5: This graph shows the results of a tightening shock in macroprudential policy on a set of bank risk and return variables conditioning on the bank business model. The response is expressed in percentage point changes. We obtain an indicator of the bank business model by performing a factor analysis on a set of bank characteristics. The first factor, which explains 63% of the variation, is related to the retail orientation of the bank, so we interact this factor with the monetary policy shock. The blue (circled) impulse responses indicate the response of banks that are classified by the factor analysis as being non-retail banks, i.e. the factor score is smaller than -0.5 (lowest 25% factor scores). The red (crossed) line impulse responses indicate the response of retail oriented banks to a macroprudential policy shock, i.e. a factor score larger than 0.5 (highest 25% factor scores). The yellow bars indicate the differential significance level between retail and non-retail impulse responses at the 90% significance level. The index that is used is the overall macroprudential index covering all policy tools. For the unconditional impulse responses we show the 95% confidence intervals. For the impulse responses of retail and non-retail banks we use 68% confidence intervals. The horizon is measured in quarters.

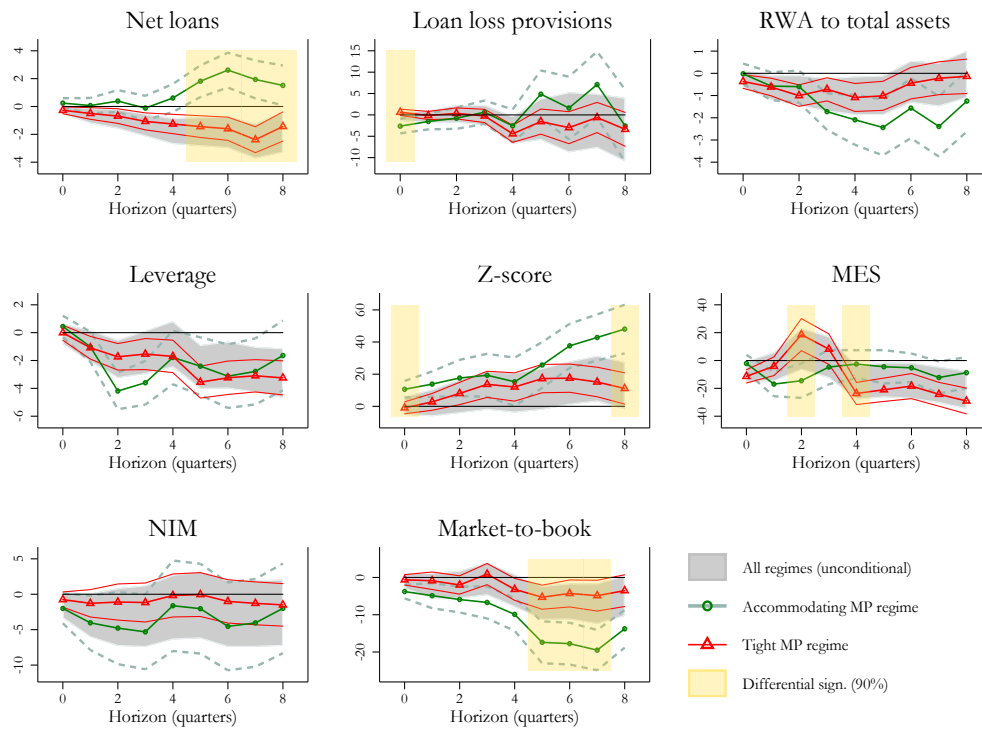


Figure 6: Impact of a tightening in the macroprudential index across different monetary policy regimes for a sample of Eurozone banks between 2008Q4 and 2018Q4 on a set of bank risk and return profile variables. The response is expressed in percentage point changes. The monetary policy shock is constructed based on the identification-through-heteroskedasticity methodology in line with Rigobon (2004) and as described in section 3.2. The monetary policy stance is calculated as the historical contribution of the monetary policy shock to changes in the 5 year Spanish CDS spread. The red (triangle) solid line indicates the response of the bank risk profile variables to a tightening in macroprudential policy conditional on the monetary policy stance being tight (i.e. the stance is below 0). The green (circle) solid line indicates the response of the bank risk profile variables to a tightening in macroprudential policy conditional on the monetary policy stance being loose (i.e. the stance is above 0). The yellow bars indicate the differential significance level between accommodating and tight monetary policy regime impulse responses at the 90% significance level. The gray area denotes the unconditional response to a macroprudential tightening. The confidence bounds for the unconditional impulse responses represent the 95% confidence intervals. For the conditional impulse responses we use 68% confidence intervals. The horizon is measured in quarters.

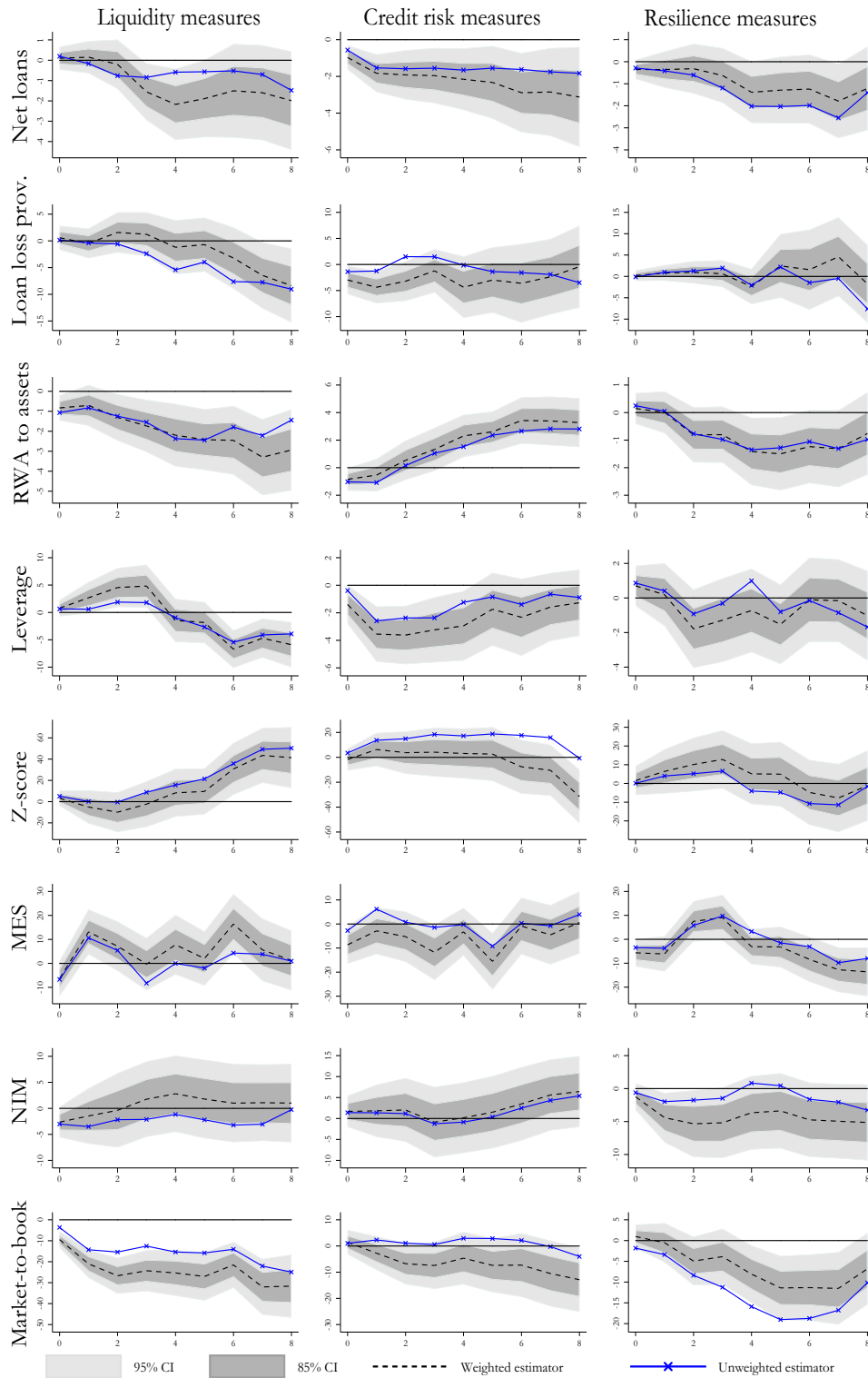


Figure 7: Robustness check : Impact of a tightening shock in different macroprudential policy tools on a set of bank risk and return profile variables. The response is expressed in percentage point changes. To estimate the responses we estimate a local projections model with weighted least squares, where the weights are defined by an inverse propensity score model, as described in section 3.1. The black dashed line represents the coefficients of this weighted estimator. The blue solid (crossed) line indicates the coefficients of the unweighted estimator. In this robustness check we subdivide the index in different subindices based on their macroprudential objective. We distinguish between liquidity measures (liquidity coverage ratios, net stable funding ratios, loan-to-deposit ratios, and other liquidity requirements), credit growth measures (loan-to-value ratios, loan-to-income ratios, debt-serv-to-income ratios, maturity and amortization restrictions and risk weights on mortgage loans and commercial loans), and resilience measures (regulations under the CRR/CRD framework, capital buffers, taxes on financial institutions and loan loss provisioning rules). The dark area represents the 85% confidence intervals. The lighter area indicates the 90% confidence intervals. The horizon is measured in quarters.

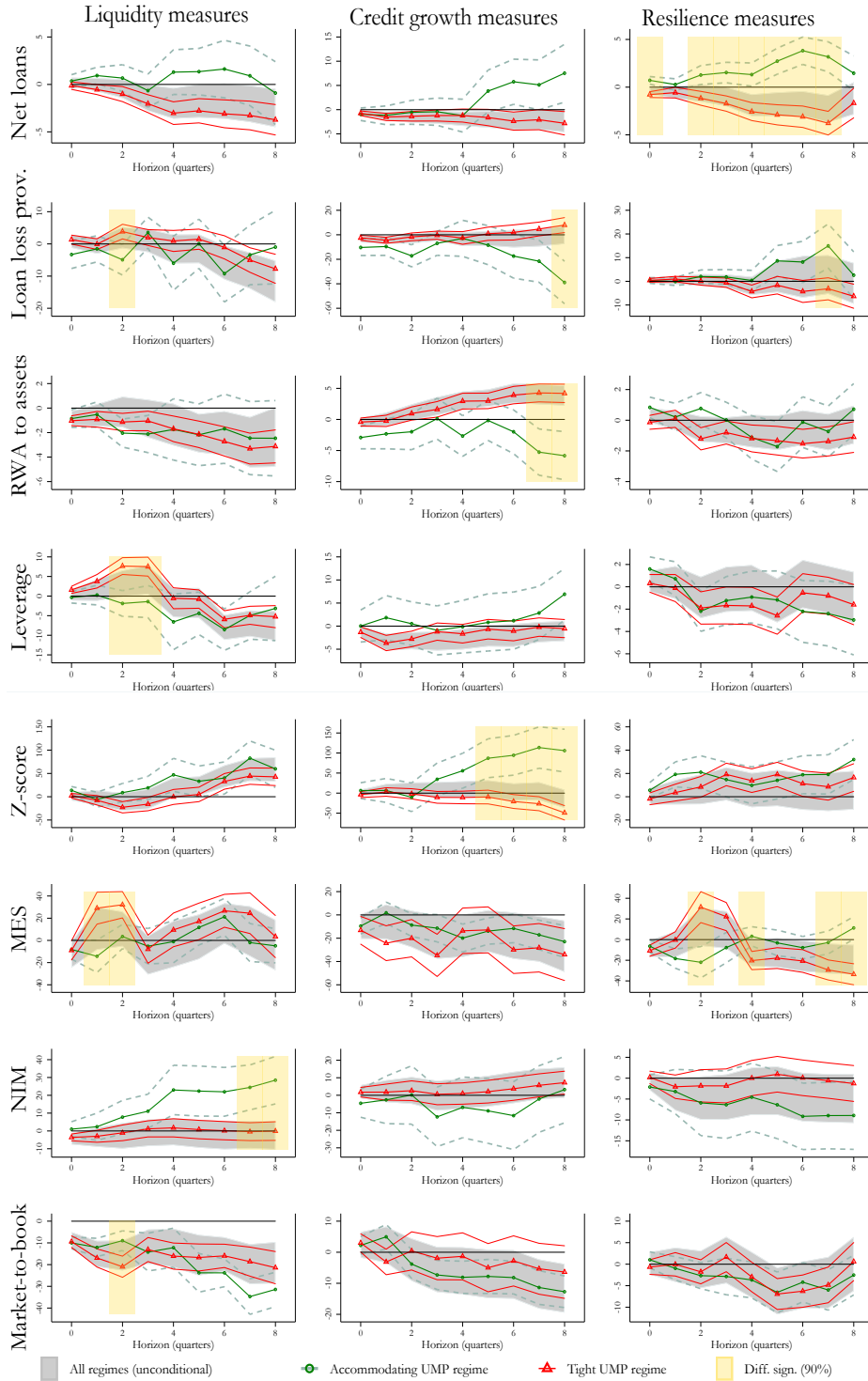


Figure 8: Robustness check : Impact of a tightening shock in different macroprudential policy tools conditional on the stance of monetary policy on a set of bank risk and return profile variables. The response is expressed in percentage point changes. To estimate the responses we estimate a local projections model with weighted least squares, where the weights are defined by an inverse propensity score model, as described in section 3.1. We subdivide the index in different subindices based on their macroprudential objective. We distinguish between liquidity measures (liquidity coverage ratios, net stable funding ratios, loan-to-deposit ratios, and other liquidity requirements), credit growth measures (loan-to-value ratios, loan-to-income ratios, debt-serv-to-income ratios, maturity and amortization restrictions and risk weights on mortgage loans and commercial loans), and resilience measures (regulations under the CRR/CRD framework, capital buffers, taxes on financial institutions and loan loss provisioning rules). The red (triangle) solid line indicates the response of the bank risk profile variables to a tightening in macroprudential policy conditional on the monetary policy stance being tight (i.e. the stance is below 0). The green (circle) solid line indicates the response of the bank risk profile variables to a tightening in macroprudential policy conditional on the monetary policy stance being loose (i.e. the stance is above 0). The yellow bars indicate the differential significance level between accommodating and tight monetary policy regime impulse responses at the 90% significance level. The gray area denotes the unconditional response to a macroprudential tightening. The confidence bounds for the unconditional impulse responses represent the 95% confidence intervals. For the conditional impulse responses we use 68% confidence intervals. The horizon is measured in quarters.

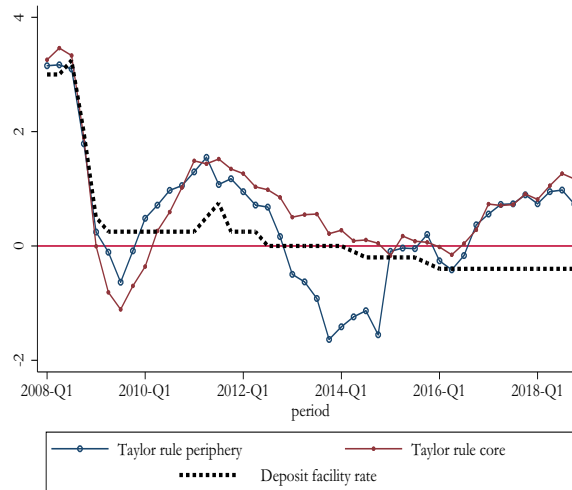


Figure 9: Taylor rule estimated for all Eurozone countries based on country-specific macroeconomic information. In this graph we show the average Taylor rule for the peripheral and core countries (blue circled and red crossed line respectively) and the deposit facility rate (black dashed line).

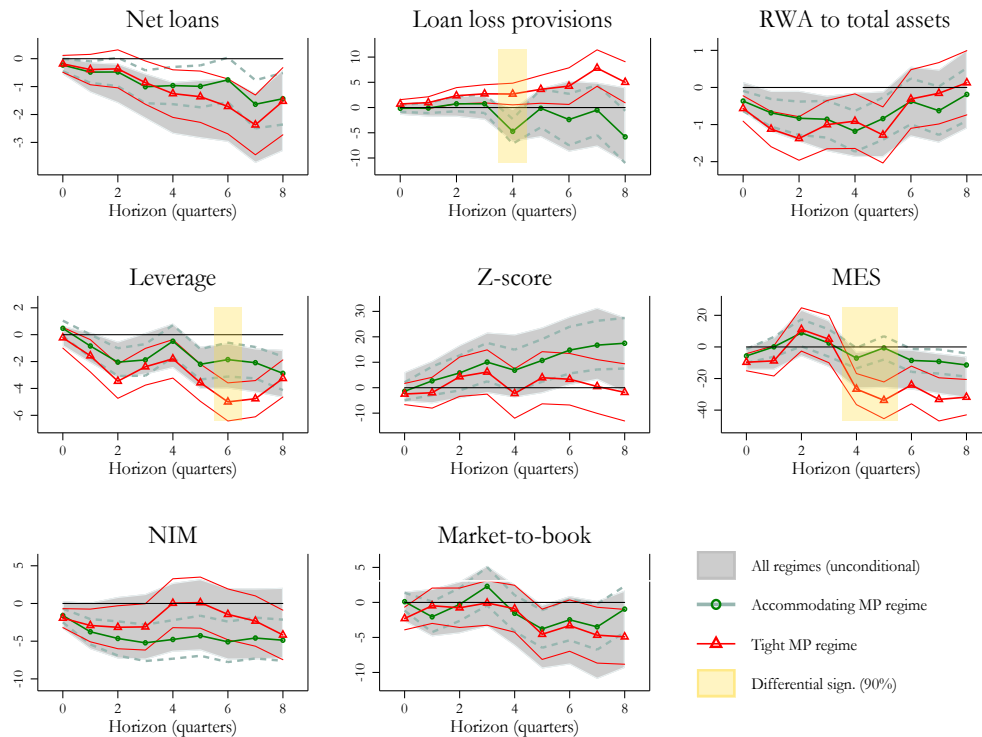


Figure 10: Robustness check: Impact of a tightening in the macroprudential index across different monetary policy regimes for a sample of Eurozone banks between 2008Q1 and 2018Q4 on a set of bank risk and return profile variables. The response is expressed in percentage point changes. To construct the monetary policy regimes we estimate a Taylor rule at the country level to account for macroeconomic differences across countries. The red (triangle) solid line indicates the response of the bank risk profile variables to a tightening in macroprudential policy conditional on the monetary policy stance being tight (i.e. the stance is below 0). The green (circle) solid line indicates the response of the bank risk profile variables to a tightening in macroprudential policy conditional on the monetary policy stance being loose (i.e. the stance is above 0). The yellow bars indicate the differential significance level between accommodating and tight monetary policy regime impulse responses at the 90% significance level. The gray area denotes the unconditional response to a macroprudential tightening. The confidence bounds for the unconditional impulse responses represent the 95% confidence intervals. For the conditional impulse responses we use 68% confidence intervals. The horizon is measured in quarters.

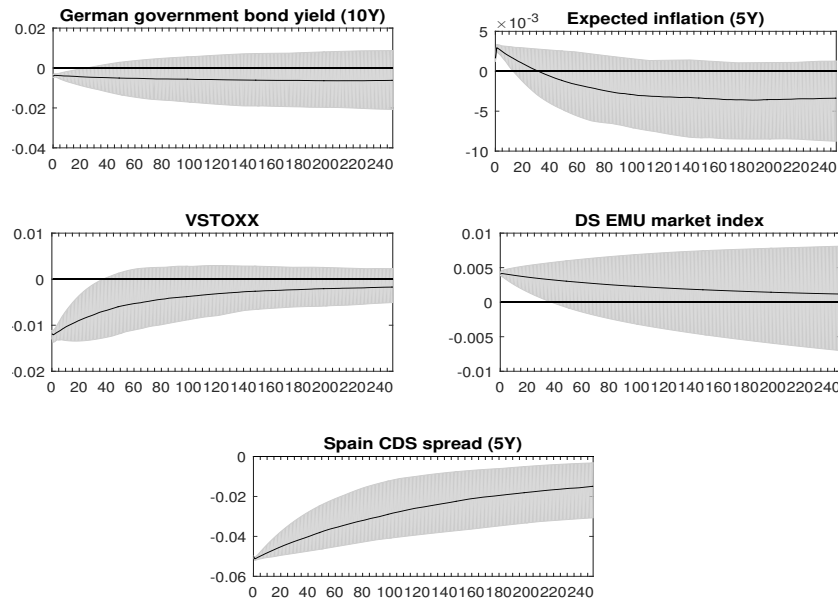


Figure 11: Impulse response function of the variables to a unit monetary policy shock which decreases the Spanish CDS spread with 5%. The monetary policy shock is obtained using the identification through external instruments approach (Stock and Watson, 2012; Mertens and Ravn, 2013; Gertler and Karadi, 2015). Gray areas represent 95% confidence intervals that are obtained through a wild bootstrap procedure. Because both the first and second stage regressions are included in the bootstrapping procedure we avoid a potential “generated regressor” problem. The horizontal axis represents the horizon of the impulse response function in working days, i.e. the IRF’s are plotted for a horizon of 240 days.

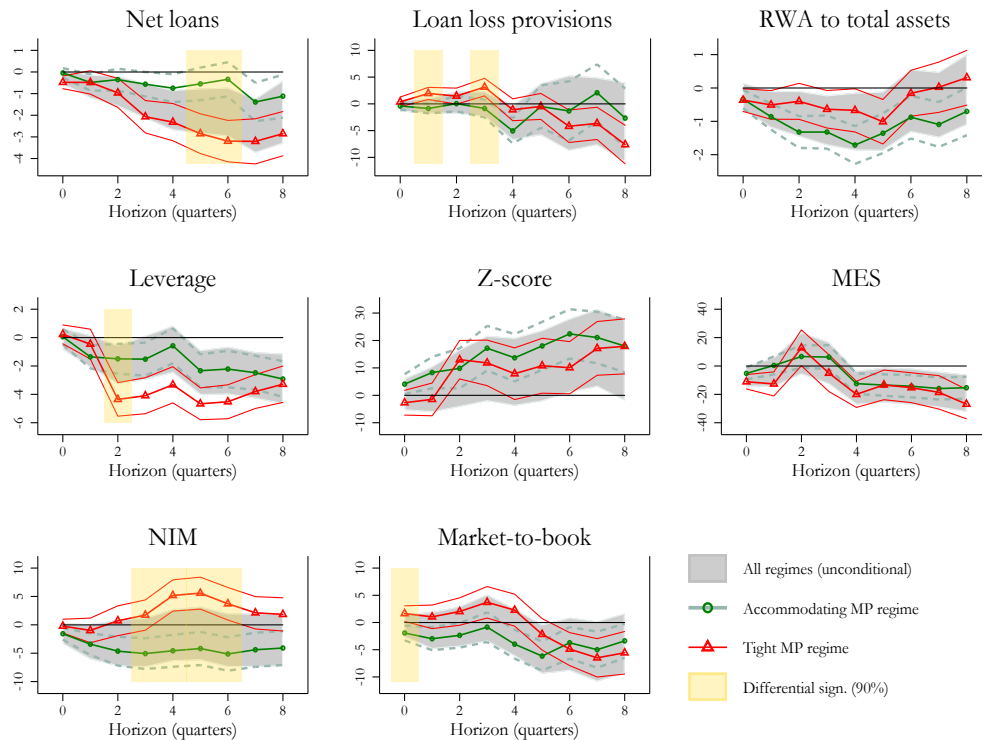


Figure 12: Robustness check: Impact of a tightening in the macroprudential index across different monetary policy regimes for a sample of Eurozone banks between 2008Q1 and 2018Q4 on a set of bank risk and return profile variables. The response is expressed in percentage point changes. The monetary policy shock is obtained using the identification through external instruments approach (Stock and Watson, 2012; Mertens and Ravn, 2013; Gertler and Karadi, 2015). The monetary policy stance is calculated as the historical contribution of the monetary policy shock to changes in the 5 year Spanish CDS spread. The red (triangle) solid line indicates the response of the bank risk profile variables to a tightening in macroprudential policy conditional on the monetary policy stance being tight (i.e. the stance is below 0). The green (circle) solid line indicates the response of the bank risk profile variables to a tightening in macroprudential policy conditional on the monetary policy stance being loose (i.e. the stance is above 0). The yellow bars indicate the differential significance level between accommodating and tight monetary policy regime impulse responses at the 90% significance level. The gray area denotes the unconditional response to a macroprudential tightening. The confidence bounds for the unconditional impulse responses represent the 95% confidence intervals. For the conditional impulse responses we use 68% confidence intervals. The horizon is measured in quarters.

Tables

<i>Factor</i>	<i>Eigenvalue</i>	<i>Proportion</i>	<i>Cumulative</i>
<i>Factor 1</i>	1.84	0.63	0.63
<i>Factor 2</i>	0.94	0.33	0.96
<i>Factor 3</i>	0.09	0.03	0.99
<i>Factor 4</i>	0.03	0.01	1.00
<i>Factor 5</i>	0.00	0.00	1.00

	<i>Correlation with characteristics</i>	<i>communality</i>
SIZE	-0.87	81%
LTA	0.39	8%
DEP	0.68	46%
DIV	-0.29	4%
ETA	0.61	35%

Table 1: This table displays the results of the factor analysis on a number of bank business model characteristics, which is conducted using the iterated principal factor method. The upper panel displays the eigenvalues of the common factors. The lower panel reports correlations of the predicted factors with the observed variables and the communality associated with each variable. A higher communality indicates that the variable is better explained by the common factors.

<i>Bank risk variables</i>	<i>Obs.</i>	<i>No. Banks</i>	<i>Mean</i>	<i>St. Dev.</i>	<i>Min.</i>	<i>Max.</i>
Net loans change	3,426	142	0.29%	3.99%	-10.68%	21.72%
Leverage change	3,425	142	-0.06%	8.82%	-27.18%	28.83%
Z-score change	3,377	140	-1.86%	55.06%	-276.06%	156.36%
Loan loss reserves change	2,173	102	2.06%	10.54%	-29.51%	58.20%
RWA to assets change	3,307	136	-0.67%	4.23%	-15.32%	13.92%
NIM change	3,426	140	2.73%	19.38%	-80.24%	95.22%
MES change	2208	63	0.26%	39.82%	-180.10%	156.70%
Market-to-book change	2257	64	-4.44%	21.52%	-84.16%	51.95%

<i>Bank controls</i>						
SIZE	3,424		17.48	1.68	13.11	21.35
DEP	3,424		0.55	0.16	0.18	0.89
LTA	3,424		0.62	0.14	0.18	0.91
CAP	3,424		0.07	0.04	0.02	0.27
DIV	3,424		0.38	0.19	0.00	1.00

<i>Macro controls</i>						
Loan growth	3,424		-1.04%	5.42%	-18.24%	31.49%
GDP growth	3,424		1.84%	3.34%	-10.03%	19.99%
House price growth	3,424		0.60%	5.51%	-16.10%	33.33%
Debt growth	3,375		-0.79%	4.15%	-15.09%	20.97%
VSTOXX	3,424		23.55	7.72	12.17	48.65
Policy rate (MRO)	3,424		0.77%	1.06%	0.00%	4.25%

Table 2: Descriptive statistics of the dependent and independent variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Annual loan growth, t-1	4.835*** (1.535)						3.499* (2.120)
Annual GDP growth,t-1		-0.010 (1.625)					-5.792 (3.832)
Annual house price growth, t-1			0.953 (1.450)				2.283 (2.416)
Annual Household debt growth, t-1				2.420*** (0.814)			0.084 (3.053)
VSTOXX, t-1					0.022 (0.016)		0.045** (0.020)
Policy rate, t-1						0.002 (0.218)	0.013 (0.455)
N	1205	1583	903	1423	1482	1596	789
R ²	0.153	0.125	0.133	0.116	0.116	0.124	0.141
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AUC	0.777	0.754	0.753	0.741	0.744	0.754	0.758

Table 3: First stage logit regression to predict a tightening in macroprudential policy. The model is estimated over the sample period 2000Q1-2018Q4 covering 19 Eurozone countries.

	(1) All policy tools	(2) Credit growth tools	(3) Liquidity tools	(4) Resilience tools
Annual loan growth, t-1	3.499* (2.120)	8.526* (4.824)	2.406 (4.192)	3.180 (3.007)
Annual GDP growth,t-1	-5.792 (3.832)	-7.882 (8.449)	0.618 (6.552)	-5.310 (4.850)
Annual house price growth, t-1	2.283 (2.416)	8.475 (5.467)	1.003 (4.846)	0.883 (3.047)
Annual Household debt growth, t-1	0.084 (3.053)	-4.966 (6.672)	4.918 (5.717)	-1.689 (4.048)
VSTOXX, t-1	0.045** (0.020)	-0.011 (0.045)	0.110*** (0.039)	0.075*** (0.026)
Policy rate, t-1	0.013 (0.455)	-0.668 (1.364)	-1.582 (1.376)	1.243* (0.642)
N	789	360	560	671
R ²	0.141	0.131	0.163	0.172
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
AUC	0.758	0.763	0.794	0.792

Table 4: First stage logit regression to predict a tightening in macroprudential policy. We perform the first stage regressions on subindices of the macroprudential index which are constructed based on their objective. The model is estimated over the sample period 2000Q1-2018Q4 covering 19 Eurozone countries.