Journal Pre-proof

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PII: S1572-3089(20)30002-4

DOI: https://doi.org/10.1016/j.jfs.2020.100724

Reference: JFS 100724

To appear in: *Journal of Financial Stability*

Received Date: 5 June 2019

Revised Date: 11 January 2020

Accepted Date: 17 January 2020

Please cite this article as: { doi: https://doi.org/

Macroprudential policy and bank systemic risk*

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Abstract

This paper investigates the effectiveness of macroprudential policy to contain the systemic risk of European banks between 2000 and 2017. We use a new database (MaPPED) collected by experts at the ECB and national central banks with narrative information on a broad range of instruments which are tracked over their life cycle. Using a dynamic panel framework at a monthly frequency we assess the impact of macroprudential tools and their design on the banks' systemic risk both in the short and the long run. We furthermore decompose the systemic risk measure in an individual bank risk component and a systemic linkage component. This is of particular interest because microprudential policy focuses on the tail risk of an individual bank while macroprudential policy targets systemic risk by addressing the interlinkages and common exposures across banks. In general, the announcements of macroprudential policy actions have a downward effect on bank systemic risk. On average, all banks benefit from macroprudential tools in terms of their individual risk. We find that credit growth tools and exposure limits exhibit the most pronounced downward effect on the individual risk component. However, we find evidence for a risk-shifting effect which is more pronounced for retail-oriented banks. The effects are heterogeneous across banks with respect to the systemic linkage component. Liquidity tools and measures aimed at increasing the resilience of banks decrease the systemic linkage of banks. Moreover, these tools appear to be most effective for distressed banks. Our results have implications for the optimal design of macroprudential instruments.

Keywords: European banks, macroprudential policy, systemic risk

JEL codes: C23, E61, E65, G10, G21, G28.

*We gratefully acknowledge helpful comments from 2 anonymous referees, Iftekhar Hasan, Martien Lamers, Gert Peersman and Gerdie Everaert, conference participants at the International Risk Management Conference 2019 in Milan, the International Finance and Banking Society 2019 Conference in Angers and seminar participants at Ghent University.

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1. Introduction

The 2008 financial crisis made clear that keeping individual financial institutions sound is not a sufficient condition to ensure financial stability. Risk and contagion in the banking sector were greatly underestimated and the Lehman episode demonstrated that the failure of one bank may cause the entire system to become unstable. Against this background, macroprudential policy tools have gained prominence in tackling the systemic risk of the banking industry. In contrast to microprudential policy which objective it is to limit bank *idiosyncratic* risk, macroprudential policy aims at reducing *systemic* risk by focusing on the risk of correlated failures and common exposures (see e.g. Crockett, 2000, Borio, 2003 and Caruana, 2010). After the crisis, a number of measures aimed at containing the stability of the financial system have been implemented across all countries in Europe.

In this paper we analyse whether macroprudential policy tools are effective in achieving the ultimate objective of maintaining financial stability in the banking sector by limiting bank systemic risk. In essence, systemic risk has two dimensions. The time dimension captures the evolution of risk over time. Banks often behave in a procyclical way which implies that systemic risk may evolve with the business cycle. The cross-sectional dimension captures the interlinkages between banks which could have an impact on the propagation of shocks through the system. These spillovers typically arise from interconnectedness caused by direct linkages between banks, e.g. through the interbank market, or by common exposures between banks. The ultimate goal of macroprudential policy is to mitigate systemic risk in both dimensions. Different tools can be used to achieve these goals, e.g. introducing countercyclical capital buffers to counter the procyclicality of bank lending or imposing exposure limits to control the interconnectedness between banks. In this paper we focus on the cross-sectional dimension of systemic risk and rely on stock market data to construct a measure of bank systemic risk. The main hypothesis is that the introduction of macroprudential tools will have a downward effect on bank systemic risk and that this will be reflected in stock market-based measures of bank systemic risk.

Thus far, the empirical evidence seems to support the use and the effectiveness of macroprudential policies. Nevertheless, most studies focus on the intermediate goals of macroprudential policy, i.e. credit growth or real estate prices. However, since containing systemic risk is the ultimate objective of macroprudential policy, we argue that the effect of the introduction of policy tools on bank systemic risk needs to be examined more directly. Moreover, from a policy perspective it is important that policymakers and supervisors understand the impact of different types of policy tools on bank risk. Second, while a number of studies focus on the impact of macroprudential policy on credit growth, it should be noted that not all tools are aimed at constraining the credit cycle but rather at increasing bank stability, e.g. liquidity rules. Again, this calls for a direct analysis of the link between different types of tools and bank stability. Third, banks may try to avoid certain regulations by transferring risk to less regulated parts of the economy, which is not captured by measures of credit growth. Yet, since banks maintain links with the non-bank financial intermediation system, regulatory arbitrage may still be reflected in market-based measures of bank systemic risk. Fourth, most studies use mixed samples of emerging and advanced economies, with the emerging countries constituting the largest part of the sample because there macroprudential policy has historically been used more frequently. Yet, it is important to establish which macroprudential tools work best in a given institutional context, therefore we focus on the European Union. Fifth, relatively few studies investigate the usage and effectiveness of policy tools during the post-crisis period. Since the increasing prominence of these tools in Europe post-2008, a deeper investigation is warranted. Finally, estimations of the impact of policy tools invariably encounter the problem of reverse causality: macroprudential policy tools may be introduced in response to increased credit growth or higher systemic risk. This normally results in an underestimation of the effectiveness of policy tools (Kuttner and Shim, 2016). The most widely used method to account for the endogeneity issue is to lag explanatory variables and to use general method of moments estimation (as in Cerutti et al., 2017, Zhang and Zoli, 2016 and Claessens et al., 2013). However, as Galati and Moessner (2018) point out, it is likely that the endogeneity problem is not mitigated in this way. In addition, most studies estimate models at a low, annual or quarterly, frequency which makes it more difficult to distinguish macroprudential policies from other policies (Galati and Moessner, 2018). We tackle this issue by using a high-frequency dynamic panel setup, by controlling for macroeconomic factors that may cause policy tools to be activated, and by carefully using the available narrative information to distinguish different types of macroprudential policy tools.

We aim to contribute to the literature by assessing the effectiveness of macroprudential policy on a sample of European banks. More specifically, we investigate the impact of macroprudential policy on bank systemic risk, which is the ultimate policy goal rather than an intermediate objective. As outlined in Bisias et al. (2012) over 30 competing systemic risk measures have been developed over the past years ranging from network analysis to macroeconomic and illiquidity indicators. Some of these measures reflect the aggregate level of systemic risk in the financial system, while others assess the individual bank's systemic risk contribution. Since macroprudential tools are directed at banks and aimed at influencing bank behavior, we estimate bank systemic risk as the bank's contribution to systemic risk, using financial market information (see e.g. Billio et al., 2012, Huang et al., 2012, Acharya et al., 2017, van Oordt and Zhou, 2019 and Adrian and Brunnermeier, 2016 for different approaches). The use of market data has several advantages compared to the use of accounting data or aggregate macro-economic variables. First, it allows us to calculate the cross-sectional, bank-specific, systemic risk contributions when the market is in the tail of its distribution. Second, market data enable a forward-looking assessment of bank risk and incorporate the expectations of market participants concerning macroprudential policy tools, including avoidance issues. Third, market data is available at a high frequency which is not the case for accounting measures. This ensures that an unexpected increase in a bank's systemic risk contribution can quickly be identified and that potential endogeneity issues are mitigated. In this paper we follow Acharya et al. (2017) and use the Marginal Expected Shortfall (MES). Over the past years, the MES has received a lot of attention by academia and regulators and it has become one of the most commonly used metrics for systemic risk in the literature. Since we want to disentangle the effect on individual bank risk and the interlinkage component, we decompose the MES into two components, capturing individual bank risk and the systemic linkage of the bank with the financial system, in line with van Oordt and Zhou (2019). This decomposition is of particular interest to answer our research question because macroprudential policy is aimed at tackling not only the risk profile of individual financial institutions but also the correlations and common exposures across institutions (Borio, 2003).

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 between 1995 and 2017. 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. In addition, the database provides information on both the announcement date and the subsequent enforcement date, which is of particular interest when using market data. In the spirit of Cerutti et al. (2017) we construct the macroprudential index as a cumulative sum of measures from the time they are announced until they are deactivated. In this way, the index reflects the macroprudential policy stance, where a higher value of the index reflects a tightening of the macroprudential stance. In contrast to other papers we also adjust the index to changes in the scope or the level of certain tools. We hypothesize that the announcement of new tools is more important than announcements concerning a change in the scope of a tool or whether the tool remains at a certain level. We do this by using different weights per type of announcement. To assess the effectiveness of different types of tools we also group tools according to their intermediate objective or include separate tools in the model.

In terms of contribution, this paper is, to the best of our knowledge, the first to explore the effects of macroprudential policy at a high (monthly) frequency in a panel data setting for listed European banks. Using monthly data at the bank level should alleviate endogeneity concerns to a maximum degree. Moreover, we focus on the impact on the banks' systemic risk, since that is ultimate objective of macroprudential policy. We use a narrative approach to carefully construct a macroprudential policy index and we distinguish different types of policy tools. Finally, we argue that the impact of policy tools may differ across bank business models, hence we exploit the variation in bank characteristics to disentangle these differential effects. The dynamics in the model also allow us to differentiate between short and long-run effects and to distinguish macroprudential policy from other policy actions. Furthermore, we control for time-varying local macroeconomic shocks by including country-specific control variables that are typically known to be used as macroprudential policy indicators. To account for global macroeconomic conditions we include time fixed effects.

The main findings of the paper can be summarized as follows. In general, the announcements of macroprudential policy actions have a downward effect on bank systemic risk. Whereas previous studies have documented a moderating effect of macroprudential measures on bank lending and real estate prices, we confirm that macroprudential policy is also effective in containing bank systemic risk as assessed by stock market investors. This is an important finding because lowering systemic bank risk is the ultimate objective of macroprudential policies. A second finding is that different types of macroprudential tools in general achieve their designated objectives. We document that borrower-oriented tools and exposure limits primarily have a beneficial impact on the individual risk component of banks. Liquidity tools and measures to increase the resilience of banks are found to lower the systemic linkage component of bank risk. We also investigate heterogeneous effects of macroprudential measures across different types of banks. We find that credit growth tools and exposure limits are found to exhibit the most pronounced downward effect for retail-oriented banks. However, for retail banks we also observe an increase in their perceived systemic linkage risk, which we attribute to risk-shifting behavior. Since lending-oriented tools force these banks to lower their exposures to certain types of counterparties or to disinvest certain types of loans or securities, these banks may shift their asset composition towards exposures that make them more vulnerable to business cycle or financial market shocks. In terms of policy, our results call for a careful calibration of lending-oriented macroprudential restrictions in order to avoid the negative consequences of risk-shifting behavior. Macroprudential policies appear to be most effective for distressed banks, i.e. banks with a high ratio of non-performing loans. The finding that their systemic linkage component decreases significantly more compared to more healthy banks is a desired policy outcome.

The paper proceeds in the following way. In section 2 we review the extant literature and develop our hypotheses. Section 3 describes the empirical setup we use to assess the effectiveness of macroprudential policy. We describe the macroprudential database, explain the construction of the macroprudential policy index and define our measures of bank systemic risk. Section 4 presents the data and the selection of the sample. In section 5 we analyze the empirical results and section 6 concludes.

2. Macroprudential policy and bank systemic risk

In this paper we test the hypothesis that macroprudential policy achieves its objective to lower the systemic risk of the banking sector. Macroprudential policy comes in various formats. In general we can distinguish two broad categories of macroprudential tools that can be classified as borrower-based and bank-based policies. Borrower-based measures refer to macroprudential instruments that focus on reducing household indebtedness, for instance loan-to-value and debt-to-income limits. Bank-based macroprudential tools capture restrictions on financial institutions, such as capital and liquidity regulations, limits on certain exposures, and changes in provisioning rules. Macroprudential measures are designed to make banks safer and this outcome should be observable by using market information. Moreover, we test whether or not the improved risk profile is observable for both bank individual risk as well as its correlation with the market. Hence, our operational testable hypothesis is that macroprudential policies are perceived by the stock market to lower the banks' individual risk and their systemic linkage. Yet, while macroprudential measures are intended to lower the banks' risk profile, banks may engage in regulatory arbitrage and avoid or circumvent certain measures. These actions may result in increased risk taking which would adversely affect their perceived risk profile. Hence, the net effect of macroprudential policy on bank riskiness is ultimately an empirical matter, which we address.

Considering the existing evidence, it can be noted that the focus of the extant literature is on the effectiveness of macroprudential policy to curb credit growth and housing prices, which can be considered as intermediate targets. Only few studies investigate the impact at the bank level. In the first group of studies, 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 that contains 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 the procyclicality. Shim et al. (2013) investigate the impact of macroprudential tools on housing credit and housing prices using a database for policy actions on housing markets 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 on 18 different policy instruments on credit growth. This dataset covers a sample of 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 the emerging economies. Akinci 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 macroprudential tools are effective in reducing the emergence of credit booms and the costs associated with credit busts. In general, most studies focusing on the intermediate objectives of macroprudential policy conclude that these policy tools achieve their stated objective, although some tools appear to be more effective than others.

However, macroprudential policy has a broader objective than restraining credit growth or housing prices. Prudential policy actions are intended to affect the balance sheet of financial institutions and in this way also financial stability (Beyer et al., 2017). Also, some tools are not aimed at curbing the credit cycle but at increasing the resilience and loss-absorbing capacity of the banks. Therefore, we investigate the heterogeneous effect of different macroprudential policy tools across different kinds of banks. For example, banks may respond to a tightening in capital requirements by issuing more equity, by increasing the retained earnings, by deleveraging or de-risking. All of these strategies should increase the loss absorbing capacity of the bank 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. All these transmission channels decrease the banks' individual risk and potentially also their interconnectedness, which should limit the occurrence of systemic crises. 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 financial 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 prevent banks to be sensitive to shocks in, e.g., real estate markets. As a consequence, a second strand of the literature has analyzed the impact of macroprudential policies at the bank-level. For example, Claessens et al. (2013) evaluate how changes in the banks' balance sheet correspond to specific macroprudential policies. They obtain a sample of 2800 banks covering 48 countries over the period 2000 to 2010. Using the same database as in Lim et al. (2011) they find that measures aimed at borrowers, such as debt-to-income caps and loan-to-value ratios, are most effective in reducing bank leverage, assets and non-core to core liabilities growth during good times. Zhang and Zoli (2016) use an event study, macro panel regressions, and micro panel regressions at the bank-level to analyse the effect of macroprudential tools in Asia. They find that find that housing-related macroprudential measures are most effective in curbing house price growth, bank loan growth and bank leverage. Altunbas et al. (2018) provide evidence based on a large panel of banks operating in 61 advanced and emerging countries. They find that macroprudential policy is indeed able to decrease bank risk. Moreover, the impact is dependent on bank-specific characteristics: small, weakly capitalized and more wholesale funded banks react more strongly to changes in the macroprudential policy stance.

Yet, the effectiveness of macroprudential policy can be jeopardized by avoidance behavior by banks and leakages as well as through unintended consequences in terms of risk shifting. For example, banks may try to engage in regulatory arbitrage when confronted with unwanted countercyclical measures or other rules which constrain bank lending or other revenue-generating financial activities. Moreover, policy strategies to increase the resilience of the banks could have detrimental effects on their profitability, which could incentivize banks to undertake activities with a lower regulatory burden. Cerutti et al. (2017) show that macroprudential policy is associated with relatively greater cross-border borrowing, suggesting that banks are trying to avoid macroprudential regulations. Reinhardt and Sowerbutts (2015) examine the effects of macroprudential regulations on international banking flows. They find that foreign banks lending to domestic non-banking sectors increases but only in response to a tightening in the domestic capital regulation and not following a tightening in the lending standards. Aiyar et al. (2014) find that foreign bank branches increase lending when regulation is tightened in the domestic country because they are excluded from domestic regulation. Next to leakage effects, risk-shifting effects could arise when banks substitute bank lending by increasing other types of (non-mortgage) unsecured exposures or by creating new products which can potentially lead to the build-up of vulnerabilities. Cizel et al. (2016) find evidence of such cross-sector substitution effects: credit provision shifts from banks towards the non-banking sector following a tightening in the macroprudential policy stance. Jiménez et al. (2017) use micro level data of the Spanish credit register and find that banks that are subject to higher requirements in dynamic provisioning shift their credit supply to riskier firms suggesting an increase in bank risk taking and a search for yield.

Ultimately, the net effect of prudential policy measures on bank systemic risk depends on the relative strength of the risk-decreasing versus the risk-shifting effects. Since stock market investors assess these effects, we rely on market-based measures of bank systemic risk to assess the perceived effectiveness of macroprudential tools to curb bank risk.

3. Methodology

In order to investigate the effect of macroprudential policy measures on bank systemic risk, we need three ingredients: (1) set up an appropriate empirical design (section 3.1), (2) construct an index which adequately captures the stance of macroprudential policy in each country (section 3.2), and (3) define our measure of bank systemic risk and its components (3.3).

3.1. Identification strategy

We assess the market perception of bank risk associated with the introduction of macroprudential policy measures using a dynamic panel setting as in, e.g. Cerutti et al. (2017) and Akinci and Olmstead-Rumsey (2018). This specification allows us to identify the immediate impact as well as the longer-run dynamics. More specifically, we estimate following dynamic panel regression model at the bank level with a monthly frequency:

$$Risk_{i,c,t} = \alpha_i + \lambda Risk_{i,c,t-1} + \theta MacroPru_{c,t} + \sum_{k=1}^{K} \beta_k Bank_{k,i,t} + \sum_{l=1}^{L} \gamma_l MacroControls_{l,c,t} + \delta_t + \varepsilon_{i,c,t} \quad (1)$$

where $Risk_{i,c,t}$ represents the (systemic) risk measure and its components of bank i and $MacroPru_{c,t}$ is the macroprudential index or a group of individual macroprudential indices in month t for country c that applies for bank i situated in country c. Because we use financial market data to measure systemic risk measures we construct the macroprudential indices on a monthly basis based on the month of the announcement of a tool. The dependent systemic risk variables are aggregated from daily to monthly frequency so that they reflect the average risk level over the entire month. If the announcement date of the tool is not available, we use the enforcement date instead. In line with Akinci and Olmstead-Rumsey (2018) and Cerutti et al. (2017) we use cumulative measures in the panel data analysis because macroprudential measures can affect the risk measures not just in the month of announcement but in subsequent months as well. We hypothesize that market participants immediately respond to changes in the macroprudential policy stance in the month of announcement, even before the tool is in force.[1] The dynamic representation allows us to distinguish these short-run (announcement) and longer-run (enforcement) effects. The short-run impact is given by coefficient θ while the long-run impact of a permanent increase in the macroprudential index is given by $\frac{\theta}{1-\lambda}$.

We estimate the baseline specification using different groupings of macroprudential tools. We estimate the model using the aggregate index where all tools are weighted equally, but we also group the tools according to their intermediate objective. In order to gain insight in the relative strength of the tools, we also perform the baseline specification including the different types of tools separately. Finally, we distinguish tools that have an explicit countercyclical design from tools that have not. The variable *Bank* represents a

[1]Since we are interested in the effect of a macroprudential change on bank systemic risk at the time of the announcement we estimate the contemporaneous effect rather than the lagged impact because we assume that the stock market immediately reacts to the macroprudential change. However, when using the lagged macroprudential index instead of the contemporaneous index the results remain unaltered.

vector of bank business model characteristics. The $MacroControls$ correspond to macroprudential indicators that are most commonly used by the macroprudential authorities to initiate policy measures.

Given that we estimate this model with a monthly frequency we have a long time series available. The Nickell bias induced by the presence of the lagged dependent variable converges to zero for a sufficiently large time dimension. Therefore, we can estimate the model by using the fixed effects estimator. A second issue arises from potential endogeneity concerns. In essence this means that the macroprudential index not only consists of exogenous changes but that new measures may be a response to changes in the macroeconomic environment. An increase in systemic risk, e.g. caused by increasing asset prices, could trigger the initiation of new macroprudential tools, potentially biasing the coefficient of interest. However, we have reasons to believe that reverse causality issues are limited. First, the model is estimated at a high frequency (monthly) which would imply that macroprudential policy has to respond within the same month to a shock in systemic risk. However, most policy decisions on the design and implementation of macroprudential tools take time. Second, the model is estimated with micro (bank level) data. Macroprudential policy is less likely to respond to individual bank behavior. However, this statement has to be nuanced, since banks may exhibit similar behavior in some episodes, which would increase the correlation between banks. Third, we explicitly control for endogenous changes in the macroprudential index by including macroeconomic and financial market variables that could trigger the usage of macroprudential policy. First, we include a variable that reflects stress in the financial markets, namely the composite indicator of systemic stress (CISS) compiled by the ESRB. When available, we use the country-level CISS to account for sovereign stress in financial markets. This approach allows us to control for the well-known bank-sovereign feedback loop which was responsible for a surge in banks' systemic risk, especially in the vulnerable Eurozone countries (De Bruyckere et al., 2013). For countries where the sovereign CISS is not available we use the euro area CISS. Next, we include the changes in bank credit to non-financial corporations to capture domestic credit growth in each country. To control for developments in the real estate market we include the year-on-year change in the country-level residential property price index. In addition, we include country-level GDP growth to account for economic activity. Finally, there is evidence that accommodating monetary policy can have an effect on bank risk-taking behavior. For example, Jiménez et al. (2014) find that a lower monetary policy rate is associated with less capitalized banks granting more loans to ex ante risky firms and banks diminish the collateral requirements from these firms in Spain. Heider et al. (2019) find that high-deposit banks lend to riskier firms compared to low-deposit banks following the introduction of negative monetary policy rates which could lead to financial vulnerabilities. For this reason, we control for the monetary policy stance in all European countries by including the corresponding central bank policy rate.

Variables at a quarterly frequency are converted to monthly data by linear interpolation. To control for global macroeconomic conditions such as global financial stress we add time fixed effects to the model. The inclusion of the local macro variables and the time fixed effects mitigate the concern of an endogeneity issue of the macroprudential index with respect to the macroeconomic cycle.

As a final effort to avoid endogeneity, we also perform the baseline regressions based on the narrative information available in the MaPPED database. This is in line with the identification approach used in Richter et al. (2018) where information on the stated objectives of policy-makers is used in order to separate policy actions with real objectives from actions with financial objectives. Since the authors analyze the effect of macroprudential tools on output and consumer prices they exclude tools with real objectives. The MaPPED database constructed by Budnik and Kleibl (2018) is particularly interesting because it also contains narrative information on the objectives of a certain policy tool. Respondents to the survey have to indicate whether or not the tools have a countercyclical design. More specifically, a measure is classified as countercyclical when "its level automatically tightens when systemic risks intensify and loosens when they fade" (Budnik and Kleibl, 2018). Since the measures designated as countercyclical explicitly refer to increasing systemic risk and since our estimations assess the relationship between macroprudential measures and bank systemic risk, this class of measures is particularly prone to endogeneity concerns. For this reason, we construct a macroprudential index that is filtered from countercyclical tools but is only based on tools that enhance the resilience of banks in an exogenous manner.

In a next step, we introduce heterogeneity across banks since we expect that the effectiveness of macroprudential measures may be related to the bank business model. Concretely, we estimate the following panel model using variables at monthly frequency:

$$\begin{aligned} Risk_{i,c,t} = {} & \alpha_i + \lambda Risk_{i,c,t-1} + \theta MacroPru_{c,t} + \sum_{k=1}^{K} \psi_k \left[MacroPru_{c,t} \times BankFactor_{k,i,t} \right] \\ & + \sum_{k=1}^{K} \beta_k BankFactor_{k,i,t} + \sum_{m=1}^{M} \gamma_m MacroControls_{m,c,t-1} + \delta_t + \varepsilon_{i,c,t} \quad (2) \end{aligned}$$

where $Risk_{i,c,t}$ represents the systemic risk measures and its components, $BankFactor_{i,t}$ is a vector of factors obtained through factor analysis that explain the bank business model and $MacroPru_{c,t}$ is the macroprudential index of country c in month t. Using this approach, we allow the impact of macroprudential policy to vary both over banks and over time, conditioning the effect on the bank's business model.

The business model characteristics in $Bank_{i,t}$ and $BankFactor_{i,t}$ are derived from the banks' balance sheets and income statements and are intended to capture the asset structure, the funding mix, capital adequacy and the income structure of the banks. However, while our panel analysis is conducted on monthly frequency, bank accounting data are only available on an annual basis. We therefore replace the value of the business model variables by their last known value of the previous month, e.g. the value reported for the end of December 2014 is used for the entire year 2015. By using the last known value prior to month t we also avoid endogeneity issues as systemic risk and market valuation may also influence a bank's business model decisions.

3.2. The macroprudential index

The macroprudential index is constructed based on the MacroPrudential Policies Evaluation Database (MaPPED) which has been collected by experts at the ECB and the national central banks.[2] MaPPED provides details on 1925 macroprudential (or similar) policy actions between 1995 and 2017 in the 28 member states of the European Union. This database has several advantages compared to existing databases (for example the IMF database as used in Lim et al. (2011), the BIS database as used in Kuttner and Shim (2016), the GMPI database as used in Cerutti et al. (2017) and the iMaPP database as used in Alam et al. (2019)). In contrast to databases that only contain information on the entering into force of a policy tool, MaPPED provides a detailed life-cycle overview of each of the policy tools. MaPPED tracks every measure over time, indicating the activation date but also changes that have been made to the scope or the level of the measure over time or the deactivation of the measure. Each policy action is classified as a loosening action, a tightening action or as an action with an ambiguous impact. Also, for every policy action, the dataset contains information on the nature of the action, for example whether the measure has a macroprudential or a microprudential nature, whether the tool has a countercyclical design, or whether the tool targets certain exposures. The tools are subdivided in 11 separate 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). An additional advantage is that 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).

We construct our macroprudential index based on the rich set of information that is available in the MaPPED database. Every tool is characterized by a unique ID code. For each of these codes the database mentions the ID code for the policy action preceding

[2]The MaPPED database is publicly available and can be found here: https://www.ecb.europa.eu/pub/research/working-papers/html/mapped.en.html

the current action and the ID code of the later action. Based on these ID codes we can link different policy tools to obtain a view on the life-cycle of every policy action. In this way the dataset of 1925 separate policy actions reduces to around 850 linked policy action 'groups'. Next, we identify a weighting scheme, whereby we assign a higher weight to policy actions we consider to be more important. Given the large variation within the different categories of policy instruments we opt to only quantify changes in the policy tool over time rather than across policy types, as in Vandenbussche et al. (2015) or Richter et al. (2018). For example, changes in the level of a tool receive a higher weight than changes in the definition of a tool. First time activations receive the highest weight. A tightening policy action is attributed with a positive value, while a loosening action is given a negative value. When the tool has an ambiguous impact, we assign a value of zero. Equally, if no action was taken in a specific quarter, we assign a value of zero to the index. Finally, we adjust the weight of the deactivation of a tool to the number of adjustments the specific tool encountered during its life-cycle. In other words, when a tool is deactivated the cumulative index for the tool drops to zero.

Type of action	**Weight**	**Loosening/tightening**	**Impact**	**Final weight (Weight x impact)**
		Policy tightening	1	1
Activation of a tool	1	Other/ambiguous impact	0	0
		Policy loosening	-1	-1
Change in the level of		Policy tightening	1	0.25
an existing tool	0.25	Other/ambiguous impact	0	0
		Policy loosening	-1	-0.25
Change in the scope of		Policy tightening	1	0.1
an existing tool	0.1	Other/ambiguous impact	0	0
		Policy loosening	-1	-0.1
Maintaining the existing		Policy tightening	1	0.05
level and scope of a tool	0.05	Other/ambiguous impact	0	0
		Policy loosening	-1	-0.05
Deactivation of a tool			Dependent on the life cycle	

Table 1: Weighting scheme to construct the life cycle of a policy action over time. Policy actions are weighted according to their relative importance. Figure 1 gives an example based on the weights displayed in this table.

Table 1 gives an overview of the weights that are used to construct the life-cycle index for every tool separately. As a typical example, figure 1 shows the build-up of policy actions over time of a loan loss provisioning rule in Romania. The tool is activated in February 1994, hence the index goes up by 1. In April 1999 and in August 2002 a tightening in the classification standards is introduced which induces an increase in the index with 0.10. In September 2005 the provisioning level is increased for loans to households which leads to an increase of the index by 0.25. At the end of 2006 the index jumps with 0.10 as the scope of the tool is extended because more entities are now required to apply. In 2008 the coefficients are raised for a second time inducing an increase of the index with 0.25. When the legal framework is relaxed in March 2009, the index goes down by 0.10. In September 2011 the tool is deactivated which means that the index goes down by 1.70, which is the cumulative sum of all policy actions over the life time of the tool. At that point in time, the index falls back to zero.

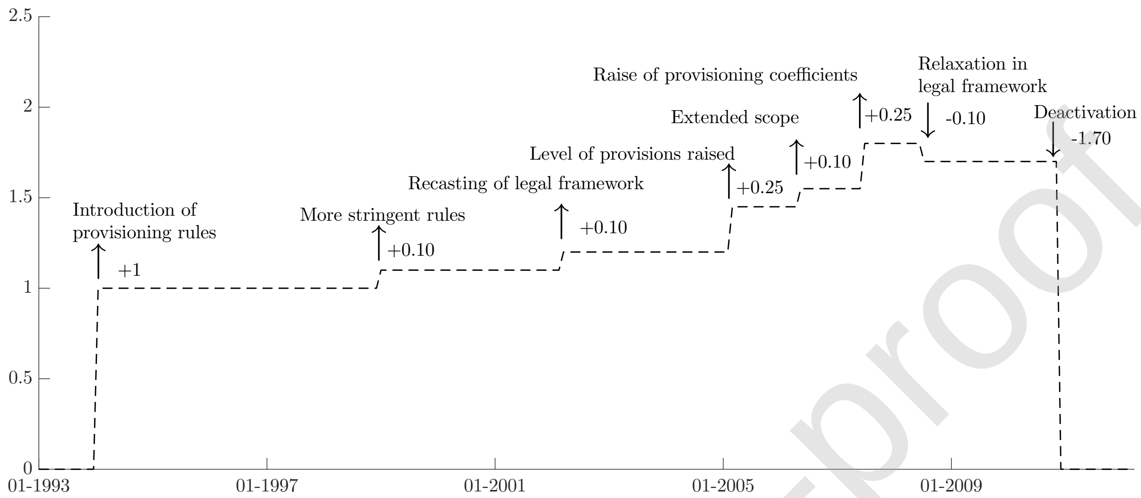

Figure 1: Illustrative example of how the macroprudential index is constructed. The graph shows the build-up of a loan-loss provisioning tool that was announced at the beginning of 1994 in Romania. At that point in time the index increases with 1. Changes in the scope which tighten the tool increase the index by 0.10. Changes in the level that have a tightening effect push the index up by 0.25. Loosening policy actions are assigned a similar weight but have a downward impact on the index. The deactivation brings the index back to zero meaning that the weight is dependent on the life cycle of the tool.

After we reconstruct the life-cycle of the 850 policy tools in a similar way, we obtain an aggregate macroprudential index that reflects the macroprudential policy stance in a certain country. We sum all categories, giving an equal weight to all tools. We acknowledge that an equal weight may not be appropriate since some tools are more effective than others, but we address this by estimating the baseline specifications by regrouping the tools in narrower categories according to their objective or by including tools separately in the model. More specifically, we investigate the impact of lending standard restrictions which incorporate loan-to- value ratios, loan-to-income ratios, debt-serve-to-income ratios and maturity and amortization restrictions. Next to this we analyze the effect of risk weights on mortgage loans and commercial loans. The lending standard restrictions and sectoral risk weights are both tools aimed at restraining credit growth. Next to this we also account for liquidity regulations. These tools cover the initiation of liquidity coverage ratios, net stable funding ratios, loan-to-deposit ratios, and other liquidity requirements. As a separate category we include the exposure limits as a policy tool which comprises single client exposure limits, intragroup exposure limits and sector and market segment exposure limits among others. Lastly, we bundle the categories that impact misaligned incentives in the banking sector. In particular, we examine the effect of 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. The category other tools is a mixture of crisis management tools, debt resolution policies and changes in the regulatory framework.

3.3. Bank systemic risk

Over the past years various measures for systemic risk have been developed. Bisias et al. (2012) provide an extensive overview of the most commonly used measures ranging from network analysis to illiquidity indicators. A broad range of these measures is based on financial market data. A commonly used approach is to model systemic risk as the contribution of a bank to systemwide stress using financial market data. One of the most frequently used measures for systemic risk is the Marginal Expected Shortfall (MES) by Acharya et al. (2017) which is calculated as the expected loss of a bank's stock price conditional on a large shock to the financial system. While the purpose of these measures is to rank banks in the cross-sectional dimension in terms of their individual risk profile, a feature which is relevant to our research questions is that the MES of a bank can be decomposed in an idiosyncratic risk component and a component capturing the interconnectedness of the bank. This feature makes the approach particularly relevant for policymakers: while microprudential policy is aimed at constraining the bank's individual risk, macroprudential policy focuses on common exposures and correlations across banks (Borio, 2003).

First, we model the bivariate process of bank and market returns in line with Brownlees and Engle (2017):

$$r_{i,t} = \sigma_{i,t}\rho_{i,t}\varepsilon_{m,t} + \sigma_{i,t}\sqrt{1-\rho_{i,t}^2}\xi_{i,t} \tag{3}$$

$$r_{m,t} = \sigma_{m,t}\varepsilon_{m,t} \tag{4}$$

$r_{i,t}$ and $r_{m,t}$ are the bank and market return, respectively. As the market return we use the MSCI Europe. $\sigma_{m,t}$ and $\sigma_{i,t}$ are the volatilities of the market and the bank i at time t respectively. $\rho_{i,t}$ is the correlation between $r_{i,t}$ and $r_{m,t}$ at time t. The disturbances ($\varepsilon_{m,t}$,$\xi_{i,t}$) are assumed to be independently and identically distributed over time and have zero mean and a unit variance. We can write the MES more explicitly as a function of correlation, volatility and the tail expectations of the standardized innovations distributions:[3]

[3]To estimate the different components of the MES we follow Brownlees and Engle (2017) and Idier et al. (2014). We explain the estimation procedure in more detail in appendix 1.

$$
\begin{aligned}
MES_{i,t} &= E_{t-1}(r_{i,t}|r_{m,t} < C) && (5)\\
&= \sigma_{i,t}\rho_{i,t}E_{t-1}\left(\varepsilon_{m,t}|\varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right) + \sigma_{i,t}\sqrt{1-\rho_{i,t}^2}E_{t-1}\left(\xi_{i,t}|\varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right) && (6)
\end{aligned}
$$

The MES measures a bank's expected equity loss when the market falls below a certain threshold over a given horizon. 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. We make the assumption that the dependence between bank and market returns is fully captured by the time-varying conditional correlations $\rho_{i,t}$. This assumption implies that the standardized innovations $\xi_{i,t}$ and $\varepsilon_{m,t}$ are assumed to be independently distributed at time t. More specifically, $E_{t-1}\left(\xi_{i,t}|\varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right)$ and thus the second part of the sum is zero. The MES now simplifies to:

$$
\begin{aligned}
MES_{i,t} &= \sigma_{i,t}\rho_{i,t}E_{t-1}\left(\varepsilon_{m,t}|\varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right) && (7)\\
&= \frac{\sigma_{i,t}}{\sigma_{m,t}}\rho_{i,t}E_{t-1}\left(r_{m,t}|r_{m,t} < C\right) && (8)\\
&= \frac{\sigma_{i,t}}{\sigma_{m,t}}\rho_{i,t}ES_{m,t} && (9)
\end{aligned}
$$

$ES_{m,t}$ denotes the Expected Shortfall of the market and reflects the expected loss of the market when the market experiences a large shock greater than threshold C. We can see that the MES is proportional to the dynamic $\beta_{i,t}$:

$$MES_{i,t} = \beta_{i,t}ES_{m,t} \tag{10}$$

where $\beta_{i,t} = \frac{cov(r_{i,t})}{var(r_{m,t})} = \rho_{i,t}\frac{\sigma_{i,t}}{\sigma_{m,t}}$ denotes the time-varying conditional beta for bank i at time t and $ES_{m,t}$ is the expected shortfall of the market. The expected shortfall of the return on the financial system, $ES_{m,t}$, is invariant across banks i which implies that the dispersion in the MES can only be attributed to cross-sectional differences in $\beta_{i,t}$. If we take the logarithmic transformation we can write the following expression:

$$log(\frac{MES_{i,t}}{ES_{m,t}}) = log(\beta_{i,t}) = \underbrace{log(\frac{\sigma_{i,t}}{\sigma_{m,t}})}_{\text{Individual risk (IR)}} + \underbrace{log(\rho_{i,t})}_{\text{Systemic linkage (SL)}} \tag{11}$$

We can now see that changes in the MES and the dynamic beta are determined by changes in the time-varying correlation with the market $\rho_{i,t}$ and changes in the standard deviation of the bank relative to the standard deviation of the market $\frac{\sigma_{i,t}}{\sigma_{m,t}}$. These terms are in line with the 'systemic linkage' component (SL) and the 'individual risk' (IR) component as described in van Oordt and Zhou (2019) so we decide to adopt the same names for both components. Notice that for the decomposition of the MES we make the assumption that there are no tail dependencies. However, in the regression analysis we calculate the MES as shown in equation 6 and we relax the assumption of independent market and bank returns. More specifically, we assume that the dependence between financial asset returns is not linear. This means that tail dependencies can occur: when the market is in its tail, the bank disturbances may be even further in the tail if there is serious risk of default (Brownlees and Engle, 2017). We can show, however, that the variation in the MES is mainly explained by variation in the first part of equation 6 and that the second part of equation 6 is close to zero. For this reason, the results of the regressions using the MES and beta as dependent variables will yield different, yet very similar results since the time fixed effects absorb all variation in the ES-component.

This decomposition is of particular interest for our research. More specifically, microprudential regulation focuses on banks' individual tail risk, while macroprudential regulation also takes correlations and common exposures across institutions into account. This decomposition allows us to assess whether or not macroprudential policy actions impact the systemic risk of the banks by affecting their individual risk, their interlinkage with the market, or both, as perceived by the stock market. In the regression analysis we therefore estimate the impact of macroprudential policy on 4 response variables: the two subcomponents of dynamic beta, IR and SL, the dynamic beta itself, and the MES.

4. Data and sample selection

To conduct our analysis we require both financial market and accounting data for a set of listed European banks. We obtain annual balance sheet and income statement data from Bankscope and daily stock return data from Datastream, which are linked based on the ISIN codes. We limit the sample to banks of which the Bankscope specialization is bank holding company, commercial bank, cooperative bank, investment bank or real estate and mortgage bank. We furthermore exclude financial holding companies that are not engaged in banking activity (e.g., asset management companies, online brokers or insurance companies). To achieve this we filter out banks that have a loans-to-assets ratio and a deposits-to-liabilities ratio lower than 20%. In addition, we manually drop domestic subsidiary banks (e.g., the listed regional branches of the French bank Crédit Agricole). Because the systemic risk measures are estimated on a daily frequency we require that the stocks in our analysis are liquidly traded by imposing that at least 65% of returns are non-zero during the sample period. We use the accounting data to construct a set of business model variables to capture the asset, liability and income structure of the banks as in Mergaerts and Vander Vennet (2016). We measure a bank's asset structure by defining variables that capture the composition of earning assets (the loan ratio, LTA) and the quality of the loan portfolio (the proportion of non-performing loans in total loans, NPL). 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 indicator for the banks' income structure, we use the share of non-interest income in total income (DIV) as a proxy for revenue diversification. Bank profitability is captured by the pre-tax income divided by total assets (ROA). We also include bank size, measured by total assets, as a control variable. Note that all variables have been winsorized at the 1% level.

The macro control variables described in section 3 (Methodology) are retrieved from the ECB Statistical Data Warehouse (SDW) and Datastream. Quarterly series are transformed into monthly series using linear interpolation techniques. After the application of the data selection procedure and the matching with the macroprudential variables and the bank characteristics our bank sample covers 113 European banks across 21 countries resulting in 15686 bank-month observations. The sample of banks is displayed in the appendix. Descriptive statistics can be found in table 2.

Variable	*Unit*	*Mean*	*Std. Dev*	*Min.*	*Max.*	*N*	*Source*
Systemic risk measures							
Individual risk		2.33	1.22	0.51	7.69	15,686	Datastream
Systemic linkage	%	41.39	22.54	0.05	83.04	15,686	Datastream
Beta		0.94	0.63	0.001	2.79	15,686	Datastream
MES	%	2.45	1.65	0.001	7.35	15,686	Datastream
PD	bps	2.78	1.44	0.58	8.30	13,402	CRI/MRI/NUS
CDS	bps	177.29	259.97	5.94	1,519.59	5,991	Markit
VaR	%	3.51	2.02	0.92	12.25	15,686	Datastream
CoVaR		0.72	0.57	0.0004	2.75	15,686	Datastream
Bank specific characteristics							
LTA	%	57.30	14.57	10.33	91.03	15,686	Bankscope
NPL	%	4.44	4.35	0.15	25.52	15,686	Bankscope
CAP	%	7.63	3.75	1.38	28.46	15,686	Bankscope
SIZE		17.47	2.25	11.38	21.14	15,686	Bankscope
ROA	%	0.64	1.49	-16.48	12.61	15,686	Bankscope
DIV	%	39.85	14.43	2.94	99.74	15,686	Bankscope
DEP	%	52.45	17.11	15.72	89.21	15,686	Bankscope
Macroprudential policy rule variables							
Loan growth	%	4.60	8.76	-20.00	64.00	15,686	SDW: MFI loans to NFC (yoy \% change)
GDP growth	%	1.45	3.02	-10.30	29.35	15,686	Real GDP growth (yoy \% change)
HPI growth		3.15	8.96	-27.00	81.00	15,686	OECD, Eurostat and NCB's (yoy \% change)
CISS		0.21	0.22	0.01	0.99	15,686	SDW: Systemic Stress Composite Indicator
Central bank policy rate	%	1.76	1.64	-0.50	11.50	15,686	Policy rate of the corresponding central bank
Macroprudential index							
MacroPru		4.18	6.23	-9.35	22.60	15,686	MAPPED
Lending standards		0.96	3.12	-5.60	11.55	15,686	MAPPED
Sectoral risk weights		0.46	0.76	-1.00	2.60	15,686	MAPPED
Credit limits		-0.44	2.07	-8.25	1.00	15,686	MAPPED
Liquidity tools		0.97	1.68	-1.25	9.00	15,686	MAPPED
Exposure limits		0.04	1.43	-3.15	4.00	15,686	MAPPED
Minimum capital		0.88	1.26	-0.90	7.10	15,686	MAPPED
Capital buffers		0.62	1.03	-1.00	4.25	15,686	MAPPED
Tax		0.31	0.72	-1.00	2.50	15,686	MAPPED
Provisioning rules		0.09	0.53	-3.30	3.00	15,686	MAPPED
Other		0.25	0.69	-2.25	7.55	15,686	MAPPED

Table 2: Descriptive statistics

In order to gain insight in the association between bank business models and the bank systemic risk components we use in our empirical analysis, table 3 exhibits the association between 7 bank characteristics and the four risk components: individual risk and systemic linkage, the dynamic beta and the MES. More specifically, we compare the characteristics of low-risk banks (lowest quartile) with those of the high-risk banks (highest quartile). For each comparison we calculate the corresponding t-value, indicating the significance of the difference. The higher the absolute value of the t-value, the more distinct the banks are in that dimension. For the individual risk component, the main discriminating variables are the non-performing loan ratio NPL and the banks' profitability ROA. This confirms the finding by van Oordt and Zhou (2019) that the individual risk measure is closely related to the probability of default of the bank. As a result, we can expect that macroprudential tools that are aimed at improving the credit risk of the bank, such as loan loss provisioning tools or borrower related tools that increase the resilience of banks by improving the collateral and by decreasing the debt levels of borrowers, will have the largest impact on the individual tail risk of the bank. Notwithstanding the finding that NPL and ROA are the most significant discriminators between high and low-risk banks, the stock market also significantly attributes a lower IR to banks characterized by a higher degree of revenue diversification, most likely because these banks are less vulnerable to persistently low interest rates. The systemic linkage component captures the correlation of the bank with the market and hence its interconnectedness. In accordance with van Oordt and Zhou (2019) and López-Espinosa et al. (2013) we find that high values for the systemic linkage component of the bank is associated with a larger bank size and with the funding structure of the bank. A bank characterized by a lower deposit funding ratio is to a larger extent financed with market-based funding sources such as interbank loans which are more interest rate sensitive. Larger banks and banks with a less stable funding base are thus more interconnected with the system. We hypothesize that liquidity regulation and capital buffers aimed at improving the resilience of systemically important banks will have a beneficial impact on the systemic linkage of the banks. Next to the funding structure and the size of the bank, more systemically linked banks have a smaller loan portfolio, are characterized by fewer non-performing loans, have a lower capital ratio, are more diversified in their income sources and have a slightly lower profitability. The correlations of the bank business model factors related to the dynamic beta and the MES are similar to the correlations of the business model characteristics with the systemic linkage component, indicating the the systemic risk measures are predominantly driven by the systemic linkage of the bank.

	IR	SL	Beta	MES	LTA	NPL	DEP	CAP	DIV	SIZE	ROA
Individual risk (IR)											
25% lowest IR banks	1.27	32.64%	0.44	1.14%	58.93%	3.54%	55.10%	8.24%	38.73%	16.69	1.13%
se	*0.29*	*0.23*	*0.34*	*0.01*	*0.13*	*0.03*	*0.17*	*0.04*	*0.14*	*2.48*	*0.01*
25% highest IR banks	4.26	31.33%	1.29	3.37%	59.31%	6.75%	57.41%	7.95%	36.21%	16.77	0.10%
se	1.34	0.21	0.84	0.02	*0.14*	*0.06*	*0.18*	*0.04*	*0.14*	*2.47*	*0.02*
Difference	-3.00	1.30%	-0.86	-2.22%	-0.38%	-3.21%	-2.31%	0.29%	2.52%	-8.43%	1.02%
T-value	-45.30	0.86	-19.41	-19.75	-0.42	**-10.38**	-1.92	1.08	2.58	-0.50	**8.91**
Systemic linkage (SL)											
25% lowest SL banks	2.49	7.79%	0.20	0.76%	59.70%	6.23%	67.46%	10.09%	36.07%	14.39	0.90%
se	*1.50*	*0.04*	*0.23*	*0.01*	*0.13*	*0.05*	*0.15*	*0.05*	*0.15*	*1.87*	*0.02*
25% highest SL banks	2.25	65.77%	1.45	3.69%	51.07%	2.90%	41.03%	5.71%	43.16%	19.47	0.71%
se	*0.86*	*0.08*	*0.51*	*0.01*	*0.17*	*0.02*	*0.13*	*0.02*	*0.14*	*1.37*	*0.01*
Difference	-0.25	57.98%	1.25	2.93%	-8.62%	-3.33%	-26.44%	-4.38%	7.09%	5.08	-0.19%
T-value	2.96	-131.64	-46.18	-36.85	8.29	11.74	**27.81**	18.06	-7.22	**-45.25**	2.14
Beta											
25% lowest Beta banks	1.92	9.44%	0.15	0.57%	59.91%	5.28%	65.40%	9.89%	36.61%	14.62	1.10%
se	*1.02*	*0.07*	*0.09*	*0.01*	*0.12*	*0.04*	*0.16*	*0.04*	*0.15*	*1.96*	*0.01*
25% highest Beta banks	3.43	57.31%	1.78	4.38%	53.81%	4.72%	44.65%	6.22%	40.04%	19.00	0.22%
se	*1.54*	*0.16*	*0.46*	*0.01*	*0.16*	*0.04*	*0.14*	*0.03*	*0.16*	*1.58*	*0.02*
Difference	-1.51	-47.87%	-1.63	-3.82%	6.22%	0.58%	20.75%	3.69%	-3.32%	-4.40	0.90%
T-value	-16.89	-58.18	-71.94	-51.67	6.23	1.91	**20.37**	14.46	-3.20	**-36.09**	8.79
MES											
25% lowest MES banks	1.88	11.85%	0.20	0.38%	60.13%	5.02%	64.67%	9.66%	36.88%	14.81	1.16%
se	*1.00*	*0.09*	*0.18*	*0.00*	*0.13*	*0.04*	*0.16*	*0.04*	*0.14*	*2.02*	*0.01*
25% highest MES banks	3.38	54.62%	1.67	4.57%	53.70%	4.64%	45.90%	6.36%	40.37%	18.71	0.30%
se	*1.58*	*0.18*	*0.56*	*0.01*	*0.16*	*0.05*	*0.15*	*0.03*	*0.15*	*1.89*	*0.02*
Difference	-1.50	-42.77%	-1.46	-4.19%	6.43%	0.38%	18.77%	3.30%	-3.49%	-3.90	0.86%
T-value	-16.57	-43.92	-51.66	-73.37	6.45	1.24	**17.76**	12.95	-3.52	**-29.18**	8.41

Table 3: Comparison of the individual risk, systemic linkage, beta and MES with bank business model characteristics. A low-risk bank has an average individual risk/systemic linkage/beta/MES in the lowest quartile of the distribution; a high-risk bank an average individual risk/systemic linkage/beta/MES in the highest quartile.

5. Results

In this section we assess the impact of the announcement of a tightening in the macroprudential policy stance on European banks' systemic risk and its components. Subsection 5.1 reports and discusses the results of the baseline regression analysis. Subsection 5.2 investigates the heterogeneous impact of macroprudential policy across different bank business models using interaction effects. In subsection 5.3 we investigate the robustness of the results and use alternative measures for bank systemic risk as well as alternative ways to calculate the macroprudential index.

5.1. Baseline results

We examine whether or not stock market investors associate the announcements of macroprudential measures in a country with a decrease in the risk profile of the affected banks. Bank risk is captured by considering the systemic risk (MES), which in turn is determined by the banks' dynamic beta (beta) and this metric can be further subdivided in an individual risk component (IR) and a systemic linkage component (SL). Table 4 shows the results of the baseline regression as displayed in equation 1.

	IR (1)	*SL* (2)	*Beta* (3)	*MES* (4)	*IR* (5)	*SL* (6)	*Beta* (7)	*MES* (8)
Lagged dependent	0.745***	0.712***	0.744***	0.689***	0.746***	0.712***	0.744***	0.688***
	(0.011)	(0.018)	(0.017)	(0.016)	(0.011)	(0.018)	(0.017)	(0.016)
MacroPru (all tools)	-0.006***	0.001	-0.005***	-0.006***				
	(0.001)	(0.001)	(0.001)	(0.002)				
MacroPru (ex countercyclical)					-0.006***	-0.0003	-0.006***	-0.008***
					(0.001)	(0.001)	(0.001)	(0.002)
SIZE	0.028***	0.016	0.041***	0.053***	0.027***	0.015	0.039***	0.051***
	(0.008)	(0.010)	(0.013)	(0.016)	(0.008)	(0.010)	(0.014)	(0.016)
LTA	-0.054*	-0.028	-0.067	-0.035	-0.049	-0.031	-0.066	-0.036
	(0.031)	(0.037)	(0.048)	(0.077)	(0.031)	(0.037)	(0.048)	(0.076)
DEP	-0.037	-0.031	-0.068	0.003	-0.038	-0.031	-0.069	0.003
	(0.028)	(0.037)	(0.048)	(0.076)	(0.028)	(0.036)	(0.048)	(0.076)
NPL	0.453***	-0.340***	0.182	0.261	0.445***	-0.362***	0.155	0.205
	(0.090)	(0.095)	(0.147)	(0.190)	(0.090)	(0.094)	(0.146)	(0.188)
DIV	-0.006	0.029	0.024	0.005	-0.010	0.028	0.019	-0.003
	(0.022)	(0.028)	(0.037)	(0.045)	(0.021)	(0.028)	(0.036)	(0.045)
CAP	-0.364**	0.639***	0.269	0.555	-0.353**	0.647***	0.286	0.585*
	(0.170)	(0.187)	(0.257)	(0.344)	(0.167)	(0.187)	(0.256)	(0.344)
ROA	-0.158	0.255	-0.146	-0.323	-0.181	0.262	-0.173	-0.348
	(0.228)	(0.253)	(0.354)	(0.458)	(0.223)	(0.252)	(0.353)	(0.460)
CISS	0.114***	0.056***	0.164***	0.202***	0.110***	0.054***	0.159***	0.196***
	(0.021)	(0.018)	(0.028)	(0.036)	(0.021)	(0.017)	(0.028)	(0.037)
House price growth	0.001***	-0.000	0.001*	0.124**	0.001***	-0.000	0.001**	0.125**
	(0.000)	(0.000)	(0.000)	(0.054)	(0.000)	(0.000)	(0.000)	(0.053)
GDP growth	-0.003**	0.005***	0.002	-0.000	-0.003**	0.005***	0.002	-0.000
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Credit growth	-0.002***	0.001***	-0.001	-0.001**	-0.002***	0.001***	-0.001	-0.001**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Policy rate	-0.002	0.016***	0.013**	0.020***	-0.002	0.016***	0.013**	0.020***
	(0.004)	(0.004)	(0.005)	(0.007)	(0.004)	(0.004)	(0.005)	(0.007)
R^2 (within)	0.780	0.629	0.680	0.637	0.780	0.629	0.680	0.637
Obs				15686				
Banks				113				
Sample period				2000-2017				
Time fixed effects				Yes				
Estimated long-run effect	-2.35%	0.35%	-1.95%	-1.93%	-2.36%	0.00%	-2.34%	-2.56%

Table 4: Baseline regression results based on equation 1 in which we estimate the effect of macroprudential policy on bank systemic risk (beta/MES) and its components (IR/SL), including bank and macro control variables. In columns 1 tot 4 the macroprudential index contains all tools, equally weighted. In columns 5 to 8 the index excludes endogenous tools that are marked as "countercyclical" in the MaPPED database. The partial adjustment model is estimated using bank fixed effects. The coefficient on the macroprudential index represents the short run impact θ, the long run impact is reflected by $\frac{\theta}{1-\lambda}$ as represented in equation 1 and as shown in the bottom row of this table. Time fixed effects are also included in the model. Standard errors are the Driscoll Kraay standard errors which are robust to general forms of cross-sectional and temporal dependence when the time dimension becomes large. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

We estimate the immediate short-run impact (captured by the coefficient on the MacroPru index) as well as the long-run impact (reported in the bottom row of table 4). The dependent variables are expressed in logarithmic scale so that we can interpret the coefficients as percentages, which allows us to quantify how macroprudential policies impact the components of bank systemic risk. First, we estimate the model using the aggregate macroprudential index, whereby all tools are equally weighted. A unit increase in the macroprudential index, which corresponds to a tightening of the macroprudential policy stance, is found to have a significant immediate impact of -0.60% on the MES, translating into a long-term impact of -1.93%. With respect to the economic significance of the results, the estimated impact is almost 1.5 times larger than the average monthly change in the MES. The beta of the banks is found to drop by 1.95% in the long run. This result indicates that, on average for all banks, macroprudential policy announcements have a beneficial effect on the banks' perceived systemic risk. Considering the components of the beta, we find that the IR component exhibits a downward effect of 0.6% in the short-run and a long-run impact of -2.35%. In economic terms, this estimated impact is almost 3 times larger than the average monthly change in the IR component. The impact on the systemic linkage component is however found to be insignificant. While we will further demonstrate that this negligible overall effect hides substantial heterogeneity across types of banks, our main finding is that macroprudential policy announcements are associated with a downward effect on the banks' systemic risk, but the risk reduction is primarily due to a perceived decrease in their individual risk, not their systemic linkage with the financial sector. In a second specification shown in table 4 we use the narrative information in the MaPPED database and construct a macroprudential index excluding all those tools that are reported as designed as countercyclical by the survey respondents. Leaving out the explicit countercyclical tools helps us to control for the endogenous response of macroprudential policy to the assessment of the systemic risk level in the economy by the macroprudential authorities. The results are similar compared to the specification which uses the index based on all tools (although the long-term impact on the MES is found to be somewhat larger, at -2.56%).

The macroprudential index contains a mix of tools with varying objectives. In table 5 we analyze whether the effectiveness of the tools depends on the design of the different types of policy actions. We split the tools into subindices based on their design features described in the MaPPED database and we assess their impact on the individual risk component (IR), the systemic linkage component (SL), dynamic beta and the MES. First, we compare general tools with tools that are targeted to certain exposures, for example real estate exposures. This mainly captures borrower-related tools such as loan-to-value ratios or exposure limits. Second, we investigate whether or not there is a difference between measures that are classified in MaPPED as legally binding versus only recommended. Third, we divide the macroprudential index in an index comprising those tools that are followed by hard sanctions in case of non-compliance and an index of tools which are not associated with sanctions. Finally, we compare tools where the enforcement date equals the announcement date with tools that are enforced with a considerable time lag of 12 months or more following the announcement date. The coefficients represent the long-run effect associated with a tightening in the index. The general finding in table 5 is that all tools are associated with a downward effect on individual bank risk, although the magnitude of the perceived impact differs somewhat across types of policy actions. The perceived risk reduction is however less present, or even absent, for the systemic linkage component of bank risk, confirming the findings of table 4. In terms of policy effectiveness as judged by stock market investors, the targeted measures outperform the general measures with respect to their perceived impact on individual bank risk (-4.2% versus 0.7%, in the long run). The other subdivisions appear less discriminatory, they all exhibit a downward effect on the banks' IR component, although it appears to be most pronounced for targeted, legally binding tools associated with hard sanctions in case of non-compliance and tools that are enforced immediately after the announcement. Our finding that targeted measures produce the most significant downward effect on banks' IR is not unexpected since they are explicitly aimed at limiting well defined exposures that are deemed by the macroprudential authorities to potentially cause excessive risk. Finally, we fail to find evidence indicating that macroprudential actions decrease the systemic linkage component of bank systemic risk. In the case of targeted measures, the effect is even positive, indicating that these measures are perceived to contain bank individual risk, but not systemic linkages caused by interconnectedness.

	IR (1)	***SL*** (2)	***Beta*** (3)	***IR*** (5)	***SL*** (6)	***Beta*** (7)	***IR*** (9)	***SL*** (10)	***Beta*** (11)	***IR*** (13)	***SL*** (14)	***Beta*** (15)
Lagged dependent	0.742***	0.711***	0.744***	0.745***	0.712***	0.744***	0.744***	0.711***	0.744***	0.747***	0.712***	0.744***
	(0.011)	(0.018)	(0.017)	(0.011)	(0.018)	(0.017)	(0.011)	(0.018)	(0.017)	(0.011)	(0.018)	(0.017)
Targeted measure	-0.042***	0.021***	-0.023***									
	(0.001)	(0.002)	(0.002)									
General measure	-0.007	-0.010*	-0.019**									
	(0.001)	(0.002)	(0.002)									
Legally binding				-0.023***	0.003	-0.023***						
				(0.001)	(0.001)	(0.001)						
Recommended				-0.019***	0.003	-0.019**						
				(0.002)	(0.002)	(0.002)						
Hard sanctions							-0.027***	0.007	-0.019***			
							(0.001)	(0.001)	(0.001)			
No hard sanctions							-0.015**	-0.006*	-0.023***			
							(0.002)	(0.001)	(0.002)			
Announcement = enforcement										-0.027***	-0.006	-0.035***
										(0.002)	(0.002)	(0.003)
Enforcement 12m after announcement										-0.015**	0.007	-0.007
										(0.001)	(0.002)	(0.002)
R^2 (within)	0.780	0.629	0.680	0.780	0.629	0.680	0.780	0.629	0.680	0.780	0.629	0.681
Obs						15686						
Banks						113						
Sample period						2000-2017						
Time fixed effects						yes						
Bank variables						yes						
Macro variables						yes						

Table 5: Baseline regression results based on equation 1 in which we estimate the effect of macroprudential policy on bank systemic risk (beta/MES) and its subcomponents (IR/SL) but with the index broken down according to different design features of macroprudential policy. We distinguish between targeted/general measures, legally binding/recommended measures, hard/no hard sanctions in case of non-compliance and measures that are announced and enforced in the same month versus tools that are enforced after 12 month or more after the announcement. The partial adjustment model is estimated using bank fixed effects. The coefficients on the macroprudential index and the subcategories represent the *long-run* coefficients as measured in equation 1 by $\frac{\theta}{1-\lambda}$. Time fixed effects are also included in the model. Standard errors are the Driscoll Kraay standard errors which are robust to general forms of cross-sectional and temporal dependence when the time dimension becomes large. Control variables are omitted from the regression table to save space. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

The next step in our analysis is to move beyond general indices and dig deeper into the effects of macroprudential actions based on their stated economic objectives. In table 6 we explore the association between different types of macroprudential tools and bank risk. Columns (1) to (4) of table 6 repeat the baseline results from table 4, for comparison purposes. In columns (5) to (8) we construct an index based on 4 types of macroprudential tools that have the same intermediate objective according to the ESRB classification: policy actions related to (1) credit growth, (2) liquidity, (3) exposure concentration and (4) bank resilience or tackling misaligned incentives.

	IR (1)	**SL** (2)	**Beta** (3)	**MES** (4)	**IR** (5)	**SL** (6)	**Beta** (7)	**MES** (8)	**IR** (9)	**SL** (10)	**Beta** (11)	**MES** (12)
Lagged dependent	0.745***	0.712***	0.744***	0.689***	0.743***	0.709***	0.743***	0.688***	0.741***	0.706***	0.740***	0.687***
	(0.011)	(0.018)	(0.017)	(0.016)	(0.011)	(0.018)	(0.017)	(0.016)	(0.011)	(0.017)	(0.016)	(0.016)
MacroPru	-0.023***	0.003	-0.019***	-0.019***								
	(0.001)	(0.001)	(0.001)	(0.002)								
Credit growth					-0.038***	0.017***	-0.023**	-0.012				
					(0.002)	(0.002)	(0.002)	(0.003)				
Lending standards									-0.042***	0.007	-0.034***	-0.015
									(0.002)	(0.002)	(0.003)	(0.005)
Sectoral risk weights									-0.019	0.0170	-0.003	-0.003
									(0.005)	(0.006)	(0.006)	(0.008)
Credit limits									0.0154	0.007	0.027	0.067
									(0.011)	(0.017)	(0.016)	(0.032)
Market liquidity					-0.011	-0.024*	-0.038**	-0.038*				
					(0.003)	(0.004)	(0.005)	(0.007)				
Liquidity tools									-0.023*	-0.034***	-0.061***	-0.051**
									(0.003)	(0.004)	(0.005)	(0.006)
Concentration					-0.023*	0.034***	0.008	-0.0003				
					(0.003)	(0.003)	(0.004)	(0.006)				
Exposure limits									-0.030**	0.044***	0.012	-0.006
									(0.003)	(0.003)	(0.004)	(0.007)
Resilience tools					-0.011	-0.013*	-0.027***	-0.022**				
					(0.002)	(0.002)	(0.003)	(0.003)				
Minimum capital									0.0115	0.031*	0.046	0.022
									(0.005)	(0.005)	(0.008)	(0.009)
Capital buffers									0.000	0.003	0.008	-0.009
									(0.004)	(0.004)	(0.006)	(0.008)
Tax									-0.046**	-0.013	-0.053	-0.057
									(0.006)	(0.007)	(0.009)	(0.013)
Provisioning rules									0.0810***	-0.013	0.0692	0.096
									(0.008)	(0.011)	(0.015)	(0.027)
Other tools									-0.011	-0.081**	-0.107***	-0.057
									(0.006)	(0.011)	(0.010)	(0.012)
R^2 (within)	0.780	0.629	0.680	0.637	0.781	0.630	0.681	0.637	0.781	0.631	0.681	0.637
Obs	15686											
Banks	113											
Sample period	2000-2017											
Time fixed effects	yes											
Bank variables	yes											
Macro variables	yes											

Table 6: Baseline regression results based on equation 1. In this table we subdivide the macroprudential index in more narrow subcategories in order to assess their impact on the systemic risk measures (beta/MES) and their subcomponents (IR/SL). Columns 1 to 4 represent the estimations using the aggregate index, columns 5-8 split the aggregate index in subcategories according to their intermediate objective and columns 9-12 represent the separate tools. The model is estimated using bank fixed effects. Time fixed effects are also included in the model. The coefficients on the macroprudential index and the subcategories represent the *long-run* coefficients as measured in equation 1 by $\frac{\theta}{1-\lambda}$. Standard errors are the Driscoll Kraay standard errors which are robust to general forms of cross-sectional and temporal dependence when the time dimension becomes large. Control variables are omitted from the regression table to save space. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

In all the specifications in table 6 we directly report the long-run effect measured by $\frac{\theta}{1-\lambda}$. Focusing on the findings for this classification of tools, we find that credit growth policies, liquidity tools and bank resilience tools are most effective in containing bank systemic risk, measured by the MES or the dynamic beta. The long-run impacts vary from a downward perceived risk shift of -2.2% (resilience tools) to -3.8 (liquidity tools). Tracing the causes of the decline in systemic risk to individual risk versus systemic linkage, we observe that credit growth tools and exposure concentration tools have the most pronounced downward effect on individual bank risk. Again, this can be explained by the fact that these tools are intended to specifically address excessive risk taken by individual banks, e.g. accumulating exposures to overheating real estate markets. However, these two types of tools are also associated with an increase in perceived systemic linkage risk, since stock market investors consider them ineffective to address the interconnectedness issue. We do find a downward impact on the SL component from market liquidity tools and tools tackling misaligned incentives, because they are perceived by stock market investors to be effective in targeting industry-wide risk dynamics. The finding that credit growth tools are associated with a perceived increase in systemic linkage risk may be attributable to risk-shifting behavior by the banks. Faced with policy measures restricting credit expansion for specific types of loans or to certain types of counterparties, banks may avoid the regulation by reallocating credit or increase their exposure to other asset classes that are not subject to the regulation (as also found by Cizel et al., 2016, Aiyar et al., 2014 and Cerutti et al., 2017 among others). Acharya et al. (2018) document that banks that are more exposed to macroprudential policy actions shift mortgage lending to corporate loans relative to the pre-policy period and that the increase is mostly targeted towards riskier borrowers. Moreover, more exposed banks increase their holdings of risky securities compared with less affected banks.

Finally, the most granular approach we implement is to investigate the refinement of the 4 types of tools into their constituent policy action announcements. This is reported in columns (9) to (12) of table 6. Within the credit growth tools the lending standards are found to be most effective in decreasing the individual risk of the banks (-4.2%) as well as their dynamic beta (-3.4%). This result is in line with Claessens et al. (2013) who find that policy aimed at borrowers, e.g. loan-to-value ratios and debt-to-income ratios, are effective in (indirectly) reducing banking system vulnerabilities. The explanation for this finding is that real estate markets are an important driver of financial cycles and as a result they may hurt banks when the cycle turns. Next to this, borrower-oriented tools face less implementation challenges.

Within the group of market liquidity measures, the announcement of liquidity tools has a pronounced downward impact on bank risk. Not only do we find an association with systemic risk measures (-5.1% for the MES and -6.1% for the dynamic beta), but also bank individual risk (-2.3%) as well as the systemic linkage component (-3.4%) are judged by the stock market to decrease as a result of the new liquidity measures. This effect is consistent with the finding by López-Espinosa et al. (2013) who document that the amount of short-term wholesale funding is a key determinant for systemic risk as measured by the $COVAR$, which is closely related to our systemic linkage component. This finding is also consistent with Banerjee and Mio (2018) who find that banks react to liquidity regulation by increasing the share of high-quality liquid assets and non-financial deposits while reducing the intra-financial loans and short-term wholesale funding. Also van Oordt and Zhou (2019) find that a larger amount of stable deposit funding is associated with a lower level of systemic linkage. Tools aimed at improving the funding risk of the banks are thus found to be an effective tool to increase financial stability. Finally, within the set of tools aimed at strengthening bank resilience and remedying misaligned incentives, the most pronounced impact is found for the other tools, which mainly comprise crisis management tools and debt resolution policies. On average, these tools decrease bank beta by more than 10% and the effect is also clearly present for the systemic linkage component. This implies that market participants assess crisis management tools such as new resolution tools or the implementation of a bail-in regime as credible. This is in line with papers such as Schäfer et al. (2016) who document that bank CDS spreads and stock prices have reacted to bail-in events in Europe or Ignatowski et al. (2014) who report that banks most affected by changes in the US bank resolution regime significantly decrease their overall risk taking. With respect to capital regulation, we do not find significant effects on bank systemic risk. This does not imply that capital regulation is not related to financial stability (see e.g. De Jonghe (2010), Baker and Wurgler (2015) and Martinez-Miera and Suarez (2012) among others). In this study, however, we are interested in the perceived market reaction to a change in capital regulation at the time of the announcement. There can be different reasons why we don't find a significant announcement effect of capital regulation on bank systemic risk. First, the announcement of capital buffers comes on top of already enforced capital regulation (Basel 3). As most banks hold capital buffers in excess of the regulatory minimum, the announcement of additional capital buffers may not impose additional constraints. Second, the announcement of SIFI buffers does not always contain new information for market participants (Abreu and Gulamhussen, 2013). Third, with respect to the announcement of countercyclical buffers the effect may be limited because most of these announcements are anticipated by financial market participants. In particular, national central banks frequently use forward guidance in their communication concerning countercyclical buffers.

5.2. Heterogeneous impact across banks

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. As a consequence, stock market investors are expected to perceive the risk-reducing effectiveness of macroprudential announcements as heterogeneous across banks. In table 8 we examine this hypothesis by interacting the macroprudential index with relevant bank business model characteristics capturing their asset and liability composition, the revenue structure, their exposure to bad loans and capital adequacy. To simplify the interpretation of the results we perform a factor analysis on the bank characteristics in table 7 in line with Mergaerts and Vander Vennet (2016).[4] This approach allows us to cluster bank characteristics into economically meaningful business model types. 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. We opt to retain the first 3 factors which explain 98% of all variation in the bank characteristics. The first factor, which explains almost half of the variation, is associated with a retail-based strategy. It positively relates to the loan, deposit and capital ratios, but is negatively related to size and income diversification. The second factor loads negatively on the loan ratio but very positively on income diversification and hence captures banks that more actively engage in non-intermediation activities. The third factor is mainly correlated with the asset quality of the bank since it is positively correlated with the non-performing loans ratio. Based on these correlations, we label the first factor *RETAIL*, the second factor *DIVERSIFICATION* and the third factor *DISTRESS*.[5] In contrast to the individual bank characteristics, the 3 factors are not correlated with each other which makes the interpretation of the results more economically intuitive.

In a next step we interact the 3 business model factors with the macroprudential index and its subcomponents. In columns (1) – (3) of table 8 we report the results based on the aggregate macroprudential index in which the policy tools are equally weighted. In the next columns, we replace the aggregate index by its constituent subindices capturing tools directed at credit growth, liquidity, exposure limits and bank resilience (as explained in the construction of table 6). For each set of estimations we report the association with IR, SL and beta. To save space, we do not report the results using the MES which are similar to the results when using the dynamic beta as dependent variable.

[4]We exclude bank ROA from the factor analysis since this variable is a result variable rather than a business model characteristic.

[5]We acknowledge that the labeling of factors is always somewhat subjective. The choice for the first two labels follows Mergaerts and Vander Vennet (2016). In our case, the "Retail" factor mainly loads on deposits (and size) so we link variation in this factor mainly to the structure of the liability and funding side, while the second "Diversification" factor relates more to the composition of the asset side and consequently also the income structure of the bank. This finding is in line with Köhler (2014) and Demirgüç-Kunt and Huizinga (2010) who find that a business model can be specified with two variables: non-deposit funding and income diversification.

Factor	*Eigenvalue*	*Proportion*	*Cumulative*
Factor 1	2.07	0.59	0.59
Factor 2	1.02	0.29	0.89
Factor 3	0.31	0.09	0.98
Factor 4	0.07	0.02	1.00
Factor 5	0.01	0.00	1.00
Factor 6	0.00	0.00	1.00

	Correlation with characteristics			
	Factor 1 ***RETAIL***	*Factor 2* ***DIVERSIFICATION***	*Factor 3* ***DISTRESS***	***Communality***
SIZE	-0.87	-0.12	0.17	80%
LTA	0.31	-0.67	-0.20	59%
DEP	0.73	-0.01	0.03	58%
NPL	0.39	0.10	0.44	35%
DIV	-0.18	0.69	-0.22	56%
ETA	0.71	0.27	-0.03	61%

Table 7: This table displays the results of the factor analysis on a number of bank business model characteristics 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 bank variables and the communality associated with each variable. A higher communality indicates that the variable is better explained by the common factors.

	Aggregate index			Credit growth			Liquidity			Exposure limits			Resilience		
	IR	**SL**	**Beta**	**IR**	**SL**	**Beta**	**IR**	**SL**	**Beta**	**IR**	**SL**	**Beta**	**IR**	**SL**	**Beta**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(12)	(13)	(14)	(15)	(16)
Lagged dependent	0.746***	0.711***	0.742***	0.745***	0.712***	0.743***	0.744***	0.706***	0.739***	0.741***	0.712***	0.743***	0.745***	0.710***	0.742***
	(0.011)	(0.019)	(0.017)	(0.011)	(0.018)	(0.017)	(0.011)	(0.018)	(0.017)	(0.011)	(0.019)	(0.017)	(0.011)	(0.018)	(0.017)
MacroPru	-0.007***	-0.0001	-0.007***	-0.010***	0.005***	-0.005*	-0.003	0.002	-0.002	-0.003	0.006**	0.001	-0.004**	-0.005**	-0.009***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)
RETAIL	-0.044***	0.015	-0.028	-0.048***	0.018	-0.029	-0.050***	0.037***	-0.014	-0.033**	0.001	-0.028	-0.059***	0.030**	-0.029
	(0.014)	(0.014)	(0.021)	(0.012)	(0.013)	(0.020)	(0.013)	(0.013)	(0.020)	(0.016)	(0.016)	(0.025)	(0.012)	(0.013)	(0.019)
DIVERSIFICATION	0.005	0.013	0.019	0.009	0.005	0.015	0.011*	-0.000	0.011	-0.028***	0.007	-0.020	0.007	0.007	0.014
	(0.008)	(0.010)	(0.012)	(0.006)	(0.007)	(0.009)	(0.006)	(0.006)	(0.008)	(0.010)	(0.014)	(0.018)	(0.006)	(0.006)	(0.009)
DISTRESS	0.051***	0.030**	0.078***	0.048***	-0.020**	0.032***	0.049***	0.011	0.062***	0.024**	-0.007	0.020	0.049***	0.002	0.052***
	(0.011)	(0.014)	(0.021)	(0.007)	(0.008)	(0.011)	(0.008)	(0.009)	(0.016)	(0.012)	(0.014)	(0.018)	(0.009)	(0.010)	(0.015)
MacroPru x *RETAIL*	-0.001	0.001***	0.001	-0.002	0.003**	0.001	-0.001	0.002	-0.00004	-0.004**	0.004*	-0.001	0.001	-0.001	0.0003
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)
MacroPru x *DIVERSIFICATION*	-0.00003	-0.0004	-0.001	-0.002	-0.002	-0.004*	-0.004	0.010***	0.004	0.007***	-0.001	0.005*	-0.0003	-0.0005	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)
MacroPru x *DISTRESS*	-0.001	-0.004***	-0.003***	-0.001	-0.003*	-0.003	-0.002	-0.018***	-0.017***	0.004*	-0.004*	0.001	-0.001	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)
R^2 (within)	0.780	0.629	0.681	0.780	0.629	0.681	0.780	0.629	0.681	0.781	0.629	0.681	0.780	0.629	0.681
Obs								15686							
Banks								113							
Sample period								2000-2017							
Time fixed effects								Yes							
Bank variables								Yes							
Macro variables								Yes							
T-value *RETAIL*	-0.75	**2.65**	0.90	-1.18	**2.46**	0.48	-0.37	0.65	-0.01	**-2.06**	**1.85**	-0.20	1.03	-0.96	0.18
T-value *DIVERSIFICATION*	-0.04	-0.51	-0.52	-1.50	-0.83	**-1.93**	-1.37	3.60	0.97	**3.62**	-0.49	**1.75**	-0.22	-0.32	-0.41
T-value *DISTRESS*	-0.73	**-4.41**	**-3.42**	-0.69	**-1.74**	-1.51	-0.70	**-6.09**	**-3.94**	**1.89**	**-1.85**	0.16	-0.92	**-3.93**	**-3.18**

Table 8: This table reports the effect of macroprudential policy on bank systemic risk based on equation 2 in which we interact the macroprudential index with the 3 bank business model factors (*RETAIL*, *DIVERSIFICATION* and *DISTRESS*) obtained by the factor analysis executed in table 7. The net effects of a tightening in macroprudential policy on bank risk are graphically shown in figure 2. The model is estimated using bank fixed effects. Time fixed effects are also included in the model. Standard errors are the Driscoll Kraay standard errors which are robust to general forms of cross-sectional and temporal dependence when the time dimension becomes large. Control variables are omitted from the regression table to save space. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

In an estimation setup with multiple interactions, the coefficient on the macroprudential index is not informative since the full effect is the sum of the standalone effect and the partial derivative of bank risk with respect to all interaction terms. The full marginal effect per bank based on equation 2 is calculated as follows:

$$\frac{\partial Risk_{i,c,t}}{\partial MacroPru_{c,t}} = \hat{\theta} + \sum_{k=1}^{3} \hat{\psi}_k BankFactor_{k,i,t} \tag{12}$$

$Bank_{j,i,t}$ is the vector of factors that explain the bank business model. From equation 12 it can be seen that we obtain a unique marginal effect per bank per year (marginal effects do not vary within each year). In figure 2 we show the histograms of the total impacts of a change in the macroprudential policy stance on the individual bank risk, the systemic linkage and the dynamic beta, based on the estimation results in table 8. The histograms capture the magnitude of the effect of policy measures on risk across the European banks and display the dispersion of the impacts. In addition, we color the bars for which more than 50% of the impacts within each bar are significant at the 1% level in dark to highlight the cases where policy actions are judged by equity investors to produce the most pronounced impact. In addition, to further illustrate the results in table 8, we display the location of the bank business model factors in the histograms. We do this by indicating bars that contain banks with, on average, a high value of one of the factors with a + and bars that contain banks with, on average, a low value with a -. For example, if banks within a certain bar have, on average, a *RETAIL*-factor value that is higher than the 75th percentile of the *RETAIL* factor, this bar is indicated with a + sign. If banks within a certain bar have, on average, a *RETAIL*-factor value that is lower than the 25th percentile of the *RETAIL* factor, this bar is indicated with a - sign. The same method is used for all 3 factors. Last, we also indicate the strength of the transmission of macroprudential policy through the bank business model factors by showing the t-values for the 3 interaction terms in the bottom rows of table 8. The higher the absolute value of the t-statistic, the more important the business model factor is in the transmission of macroprudential policy to the systemic risk measures. This visually corresponds to more + signs or - signs in figure 2 that are clustered around significant bars situated at one side of the histogram.

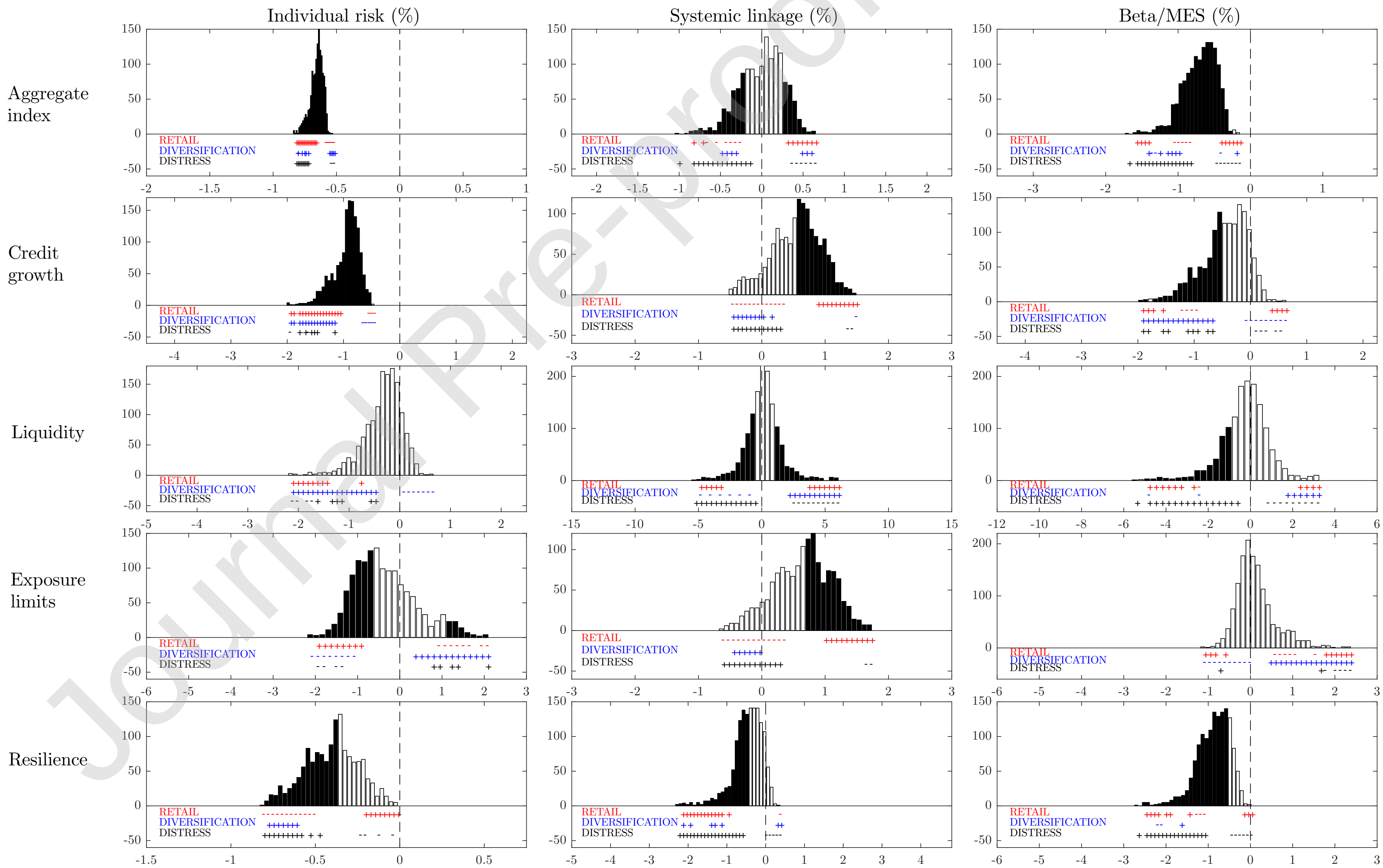

Figure 2: Histograms for the total impact of a unit increase (tightening) in the macroprudential stance on individual risk, systemic linkage and beta (in percentages) over a one-month horizon. The dark parts of the histogram bars represent bars for which more than 75% of the total impacts are significant at the 1% level. *RETAIL* reflects the retail orientation of the bank and is related to the funding structure and size of the bank. *DIVERSIFICATION* reflects the income diversification of the bank and positively relates to the income diversification and negatively to the proportion of loans. *DISTRESS* captures the asset quality of the bank. This factor loads positively on the non-performing loans to total loans ratio. Bars that contain banks which exhibit, on average, a high value (>75$^{\text{th}}$ percentile) for one of the factors are indicated with a '+' and bars that contain banks with, on average, a low value of one of the factors (<25$^{\text{th}}$ percentile) are indicated with a '-'.

For the aggregate macroprudential index (first row in figure 2) we find that the total impact of policy measures exhibits a downward effect on the systemic risk of the banks (beta/MES) and that this is primarily driven by lower individual risk. Moreover, the top left panel shows that the downward impact on IR is very concentrated, i.e. negative with a very small dispersion. Technically, the interpretation is that policy actions are associated with a significantly lower variation of the banks' stock returns relative to the standard deviation in total stock market returns, which indicates that investors recognize that the macroprudential policy actions make the banks more stable. This is evidence that macroprudential measures are interpreted by the stock market as very effective tools to contain the idiosyncratic risk of European banks. For the systemic linkage component of bank risk, the evidence is mixed, some banks exhibit a significant downward shift of SL, others are perceived to become more correlated with the market. Hence, the ultimate effect of macroprudential measures on SL across bank business models differs across banks.

Next, we investigate which bank business models are impacted most by macroprudential policy tools. For this we need to focus on the interaction terms between the macroprudential index and the bank business model factors in table 8 as well as on the distribution of the bank business model factors (location of the + and – signs) in figure 2. To illustrate the interpretation process, we first consider the results for the aggregate index. Visual inspection of the first row of panels in figure 2 indicates that a macroprudential tightening is associated with a decrease of the individual risk component (all banks are situated firmly left of zero), an insignificant effect on the systemic linkage component (banks are evenly distributed left and right of zero), resulting in a downward effect on the systemic risk of the banks (beta/MES). These graphical findings are confirmed by the coefficients in columns (1) – (3) in table 8, significantly negative for IR, insignificant for SL, yielding a significant negative effect on systemic risk (beta in column 3). Next, we focus on the interaction effects with the RETAIL factor. Although the top left panel in figure 2 shows that the most retail-oriented banks (those with a + sign) are situated to the left of the impact distribution of the individual risk component, the dispersion across banks is insufficient to make this effect significant, hence the interaction term of RETAIL with the macroprudential index remains insignificant in column (1) of table 8. The coefficient on the interaction term for the systemic linkage component, however, is positive and significant and this is reflected in the finding that retail banks are situated right of zero for the SL component in the middle top panel in figure 2, indicating an increase of their systemic linkage risk. The resulting net effect on beta/MES is insignificant for the RETAIL factor because these banks are situated on both ends of the impact distribution.

When we apply this procedure for interpreting the combined findings in table 8 and figure 2 and when we only consider the significant interaction terms, the following picture emerges. First, for the RETAIL banks, i.e. those primarily engaged in traditional intermediation activities, the left panels of figure 2 indicate that the strongest downward effect of macroprudential measures on the IR component stem from credit growth measures and exposure limits (the RETAIL + signs are situated on the left side of the impact distribution, although in table 8 only the interaction term with exposure limits is significant). These findings confirm that measures aimed at curbing specific lending exposures are interpreted by the stock market as effective tools to decrease the idiosyncratic risk of retail banks. However, when we consider the SL component (middle panels of figure 2), the banks with the highest loadings (+ signs) on the RETAIL factor are associated with an increase in their perceived systemic linkage risk precisely for the credit growth and exposure limit tools. Both interactions terms also carry a positive and significant coefficient in table 8. 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 strong substitution effects. In addition, banks may become more similar. Because of macroprudential restrictions, banks may be forced to increase their exposures to common counterparties or assets of similar risk. This may in turn increase the probability of contagion because regulation then leads to common exposures, not diversification. The increase in the SL component indicates that stock market investors are aware that retail banks may become more vulnerable to business cycle shocks. 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.

Second, for the banks with a high loading on the DIVERSIFICATION factor, the combined findings in table 8 and figure 2 can be summarized as follows. The interaction term with macroprudential policy indicates a downward effect on beta/MES for the credit growth tools which is more pronounced for more diversified banks. As can be seen from the left panel of figure 2 this risk-reducing effect for more diversified banks is clearly driven by the individual risk component. This finding is expected since these banks are less dependent on lending and hence are less affected by credit growth restrictions. Yet, for the exposure limit actions, the effect on systemic risk for diversified banks is positive and marginally significant and is driven entirely by a higher perceived individual risk. A possible explanation is that this type of measures is seen to force diversified banks to become over-reliant on non-interest income. Previous studies have shown that non-interest activities are more volatile and not associated with better performance (Stiroh and Rumble, 2006) and lead to higher income volatility (Stiroh, 2004). For European banks, Baele et al. (2007) find that the systematic risk of banks is positively associated with various indicators of bank diversification, including the non-interest income share (see also Lepetit et al. (2008)), while Köhler (2014) reports that an increasing share of non-interest income makes investment-oriented banks more risky. The most pronounced effect for the DIVERSIFICATION factor is the positive association between the liquidity measures and the systemic linkage risk component of these banks. The interaction term in table 8 is very significant and in the middle panel of figure 2 the + signs for these banks are firmly situated at the right hand side of the net impact distribution. Imposing additional liquidity constraints forces these banks to increase their exposure to financial market movements (more securities holdings on the asset side to comply with the liquidity coverage ratio and/or more market-based long-term funding at the liability side to comply with the net stable funding ratio) which stock markets interpret as increasing the systemic linkage risk of the banks.

Finally, we examine the DISTRESSED banks, i.e. those banks with a high loading on NPL. When macroprudential authorities announce actions, their objective is to lower the risk profile of the banks. An important issue is how stock markets perceive the effectiveness of these policy actions for the weakest banks. The results are broadly encouraging. In table 8, the interaction term of beta with the aggregate macroprudential index is significantly negative and this is predominantly caused by the negative coefficients for both the liquidity measures and the resilience tools. Moreover, this downward effect on the banks' risk is entirely driven by a lowering of the SL component. Notice that these negative coefficients exhibit the highest t-values (bottom panel of table 8). Likewise, in figure 2 the + signs for the DISTRESSED factor are situated on the left side of the impact distribution for beta/MES and SL for the aggregate index as well as for the indices based on liquidity and resilience actions. The interpretation is clear. Additional liquidity and resilience requirements are judged as effective in making the weakest banks more resistant to shocks and this is interpreted by stock market investors as decreasing these banks' vulnerability to systemic contagion.

The findings in table 8 and figure 2 confirm all previous results. Macroprudential actions are associated with a downward impact on the systemic risk of the banks, measured as beta/MES, and this holds for the aggregate index as well as the indices for credit growth and resilience measures. This conclusion follows from the significantly negative coefficient on the macroprudential index in table 8 and from the dark bars (with the most significant results) which are situated on the left side of the net impact distribution in figure 2. Moreover, the effect on the systemic risk of the banks is perceived a mainly driven by a downward shift of the individual risk component. In figure 2 the distribution for the impact of the aggregate index on IR is entirely situated in negative territory and it is moreover very narrow indicating a common effect across all banks. The effect on the systemic linkage component, on the other hand, is mixed, with some dark bars situated left of zero, while some indicate an increase of the SL component, which we argue is caused by risk-shifting behavior.

5.3. Robustness checks

A standard concern is that the results are driven by our choices for measurement of the main variables, namely the macroprudential index and the bank risk variables. Therefore we check whether alternative measures corroborate our findings. We also perform a subsample analysis in which we subdivide our sample according to geographical areas and time periods (pre/post crisis) and we investigate whether there are asymmetric effects when comparing policy tightenings with policy loosenings.

As a first robustness check we use alternative measures to capture the individual risk of a bank. As a first alternative measure we use the 5-year CDS spread of the banks which are taken from Markit. The CDS spread reflects the credit risk of a bank. As a second measure we use the probability of default (PD) of the banks. The PD is estimated using macro-financial and firm-specific information and is taken from the CRI/MRI database which is publicly available.[6] To align the results with the 5-year CDS spread we use the 60-month PD value. Third, value-at-risk is used as a measure for bank individual risk. As an alternative measure for the systemic linkage of the bank we calculate the CoVaR of the bank as in Adrian and Brunnermeier (2016). The CoVaR reflects the risk of the financial system when a financial institution is in distress relative to the median state. The results are displayed in table 9. From this table we can conclude that the results are robust to alternative measures for individual risk and systemic linkage.

[6]Data can be downloaded from https://www.rmicri.org/en/

	Individual risk				Systemic linkage		Individual risk				Systemic linkage		Individual risk				Systemic linkage	
	IR	**CDS**	**PD**	**VaR**	**SL**	**CoVaR**	**IR**	**CDS**	**PD**	**VaR**	**SL**	**CoVaR**	**IR**	**CDS**	**PD**	**VaR**	**SL**	**CoVaR**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Lagged dependent	0.745***	0.882***	0.910***	0.753***	0.712***	0.702***	0.743***	0.876***	0.909***	0.752***	0.709***	0.698***	0.741***	0.874***	0.905***	0.749***	0.706***	0.696***
	(0.011)	(0.016)	(0.008)	(0.011)	(0.018)	(0.019)	(0.011)	(0.016)	(0.008)	(0.011)	(0.018)	(0.019)	(0.011)	(0.016)	(0.008)	(0.011)	(0.017)	(0.018)
MacroPru	-0.023***	-0.008	-0.022*	-0.024***	0.003	0.003												
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)												
Credit growth							-0.038***	-0.056***	-0.043	-0.040***	0.017***	0.016***						
							(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)						
Lending standards													-0.042***	-0.047**	-0.042	-0.043***	0.007	0.009
													(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Sectoral risk weights													-0.019	-0.071*	-0.094**	-0.019	0.0170	0.0164
													(0.005)	(0.005)	(0.003)	(0.005)	(0.006)	(0.006)
Credit limits													0.015	0.0873	0.2105	0.016	0.007	0.007
													(0.011)	(0.023)	(0.015)	(0.011)	(0.017)	(0.018)
Market liquidity							-0.011	0.040	-0.021	-0.012	-0.024*	-0.023**						
							(0.003)	(0.005)	(0.002)	(0.004)	(0.004)	(0.004)						
Liquidity tools													-0.023*	0.016	-0.010	-0.023*	-0.034***	-0.032***
													(0.003)	(0.005)	(0.003)	(0.003)	(0.004)	(0.004)
Concentration							-0.023*	-0.064**	0.011	-0.024*	0.034***	0.036***						
							(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)						
Exposure limits													-0.030**	-0.095**	-0.031	-0.031**	0.044***	0.046***
													(0.003)	(0.006)	(0.003)	(0.004)	(0.003)	(0.003)
Resilience tools							-0.011	0.008	-0.010	-0.012	-0.013*	-0.016*						
							(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)						
Minimum capital													0.012	0.071	-0.005	0.016	0.031*	0.029
													(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)
Capital buffers													-0.0003	0.011	-0.002	-0.001	0.003	0.003
													(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Tax													-0.046**	-0.079	-0.126**	-0.047**	-0.013	-0.013
													(0.006)	(0.009)	(0.006)	(0.005)	(0.007)	(0.007)
Provisioning rules													0.081***	0.484***	0.010	0.088***	-0.013	-0.013
													(0.008)	(0.022)	(0.006)	(0.008)	(0.011)	(0.012)
Other													-0.011	-0.007	0.07	-0.023	-0.081**	-0.078**
													(0.006)	(0.007)	(0.008)	(0.007)	(0.011)	(0.012)
R^2 (within)	0.78	0.99	0.887	0.804	0.629	0.865	0.780	0.990	0.887	0.804	0.630	0.866	0.781	0.990	0.887	0.804	0.631	0.866
Obs	15686	5912	13387	15686	15686	15686	15686	5912	13387	15686	15686	15686	15686	5912	13387	15686	15686	15686
Banks	113	45	97	113	113	113	113	45	97	113	113	113	113	45	97	113	113	113
Time fixed effects										Yes								
Bank variables										Yes								
Macro variables										Yes								

Table 9: Robustness check whereby the baseline model is estimated using alternative measures that capture individual risk, namely the CDS spread, the PD and the VaR. As alternative measures for the systemic linkage we use the CoVaR. The model is estimated using bank fixed effects. Time fixed effects are also included in the model. The coefficients on the macroprudential index and the subcategories represent the *long-run* coefficients as measured in equation 1 by $\frac{\theta}{1-\lambda}$. Standard errors are the Driscoll Kraay standard errors which are robust to general forms of cross-sectional and temporal dependence when the time dimension becomes large. Control variables are omitted from the regression table to save space. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

As a second robustness check we construct the macroprudential index in an alternative way. More specifically, we recode the index based on a 'policy-on' or 'policy-off' procedure. When a specific tools is activated, the index goes up by 1. When the tool is deactivated the index drops to zero. The results are displayed in table 10. The results are again comparable to the results obtained in table 6 indicating that the activation of a tool is the most important event in the life cycle of a policy tool.

	IR (1)	**SL** (2)	**Beta** (3)	**MES** (4)	**IR** (5)	**SL** (6)	**Beta** (7)	**MES** (8)	**IR** (9)	**SL** (10)	**Beta** (11)	**MES** (12)
Lagged dependent	0.745***	0.712***	0.743***	0.6877***	0.742***	0.707***	0.741***	0.687***	0.743***	0.705***	0.739***	0.685***
	(0.011)	(0.018)	(0.017)	(0.0161)	(0.011)	(0.018)	(0.017)	(0.016)	(0.011)	(0.017)	(0.017)	(0.016)
MacroPru	-0.019***	-0.001	-0.023***	-0.022***								
	(0.001)	(0.001)	(0.001)	(0.002)								
Credit growth					-0.046***	0.017***	-0.027***	-0.012				
					(0.002)	(0.002)	(0.002)	(0.004)				
Lending standards									-0.035***	0.001	-0.034***	-0.031**
									(0.002)	(0.002)	(0.003)	(0.004)
Sectoral risk weights									-0.031*	0.017	-0.015	0.016
									(0.005)	(0.006)	(0.007)	(0.009)
Credit limits									-0.011	0.031	0.023	0.1269
									(0.016)	(0.021)	(0.017)	(0.036)
Market liquidity					-0.003	-0.030**	-0.038*	-0.041*				
					(0.003)	(0.004)	(0.005)	(0.007)				
Liquidity tools									-0.027*	-0.037***	-0.065***	-0.066***
									(0.004)	(0.004)	(0.005)	(0.007)
Concentration					-0.019	0.034***	0.012	0.006				
					(0.003)	(0.003)	(0.004)	(0.006)				
Exposure limits									-0.011	0.034***	0.023	-0.006
									(0.003)	(0.003)	(0.004)	(0.006)
Resilience tools					-0.015*	-0.023**	-0.042***	-0.038***				
					(0.002)	(0.003)	(0.003)	(0.004)				
Minimum capital									0.004	0.031*	0.034	0.0222
									(0.005)	(0.005)	(0.008)	(0.009)
Capital buffers									-0.003	-0.006	-0.007	-0.0285
									(0.005)	(0.004)	(0.006)	(0.009)
Tax									-0.042	-0.010	-0.042	-0.022
									(0.007)	(0.008)	(0.010)	(0.012)
Provisioning rules									0.089**	-0.084**	-0.003	-0.053
									(0.011)	(0.012)	(0.016)	(0.027)
Other tools									-0.011	-0.098***	-0.126***	-0.069**
									(0.005)	(0.009)	(0.008)	(0.010)
R^2 (within)	0.780	0.629	0.681	0.637	0.781	0.630	0.681	0.637	0.780	0.631	0.682	0.637
Obs	15686											
banks	113											
Sample period	2000-2017											
Time fixed effects	Yes											
Bank variables	Yes											
Macro variables	Yes											

Table 10: Robustness check in which the macroprudential index is alternatively constructed using dummies that can only take the values of 0, 1 indicating whether a tool is in place or not. The model is estimated using bank fixed effects. Time fixed effects are also included in the model. The coefficients on the macroprudential index and the subcategories represent the *long-run* coefficients as measured in equation 1 by $\frac{\theta}{1-\lambda}$. Standard errors are the Driscoll Kraay standard errors which are robust to general forms of cross-sectional and temporal dependence when the time dimension becomes large. Control variables are omitted from the regression table to save space. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

As a third robustness check we analyze whether or not the impact of macroprudential policy differs across geographical regions, across periods or whether there are asymmetric effects when comparing policy tightenings with policy loosenings. To investigate the differences across regions we create regional dummies which we interact with the macroprudential index. We distinguish 4 regions: core Eurozone countries (Austria, Belgium France, The Netherlands, Germany) and the UK, the peripheral Eurozone countries (Spain, Italy, Greece, Portugal, Malta, Cyprus and Ireland), the Scandinavian countries (Denmark, Sweden and Finland) and the Central and Eastern European countries (CEEC) (Romania, Hungary, Czech Republic, Bulgaria and Poland). The results can be found in table 11 (first four columns). We include the macroprudential index and the interaction terms between the index and the periphery dummy, the Scandinavian dummy and the CEEC dummy. The coefficients on the index itself capture the impact of a macroprudential tightening in the core countries on the systemic risk measures and serves as a benchmark to compare the impact of macroprudential policy in the other regions. In the core countries, macroprudential policy has a downward effect on banks' individual risk, as perceived by the market. Macroprudential policy appears to have no immediate impact on the systemic linkage of banks situated in core Europe. In the peripheral countries the impact of macroprudential tools on the individual risk is limited: the coefficient on the benchmark and on the interaction term cancel each other out. On the other hand, in the peripheral countries the impact on the systemic linkage component is more pronounced: a tightening in macroprudential policy leads to a reduction in the systemic linkage component of 1.7%. In the Scandinavian countries banks do not seem to benefit from macroprudential policy as the systemic linkage even increases following a tightening in the macroprudential policy stance. Last, the CEEC countries benefit most in terms of individual risk as this component drops by 3% in response to macroprudential policy. This translates into a downward effect on the beta/MES of around -3% as the systemic linkage does not respond to changes in macroprudential policy.

Next, we investigate whether the impact of macroprudential policy differs across different time periods in the next 4 columns of table 11. We therefore divide the sample into 3 different periods: the pre-crisis period running from 2000 to end 2007, the crisis period from 2008 to 2010 and the post-crisis period going from 2011 to the end of 2017. We use the pre-crisis period as the benchmark period in these regressions. Before 2008, macroprudential tightenings are associated with a decrease in the individual risk but an increase in the systemic linkage component, resulting in a limited net effect. During the crisis period, the effects on the systemic risk measures are not significantly different from the effects during the pre-risis periods. It appears that during the post-crisis period, from 2011 onward, macroprudential policy benefits all components of systemic risk indicating that macroprudential policy is getting more effective and that the tools which are announced in this period have the desired impact.

Last, we analyse the presence of asymmetric effects with respect to tightening and loosening policy measures. We therefore create two new indices that reflect only tools that are tightening in nature (MacroPru tightening), and an index that captures measures that had the objective to loosen the macroprudential policy stance (MacroPru loosening). For the latter index we denote loosenings by positive weightings instead of negative ones to make the results more comprehensible. The MacroPru loosening index contains for example relaxations in the level of a certain tool, which receives a weight of 0.25, but it

	IR (1)	*SL* (2)	*Beta* (3)	*MES* (4)	*IR* (5)	*SL* (6)	*Beta* (7)	*MES* (8)	*IR* (9)	*SL* (10)	*Beta* (11)	*MES* (12)
Lagged dependent	0.740***	0.709***	0.743***	0.688***	0.744***	0.712***	0.743***	0.688***	0.744***	0.711***	0.742***	0.688***
	(0.011)	(0.018)	(0.017)	(0.016)	(0.011)	(0.018)	(0.017)	(0.016)	(0.011)	(0.018)	(0.017)	(0.016)
MacroPru Core countries	-0.019***	-0.00003	-0.019***	-0.012*								
	(0.001)	(0.001)	-0.002	(0.002)								
MacroPru × *Periphery countries*	0.023***	-0.017**	0.004	-0.009								
	(0.002)	(0.002)	(0.003)	(0.003)								
MacroPru × *Scandinavian countries*	-0.007	0.010**	0.004	-0.003								
	(0.001)	(0.001)	(0.002)	(0.002)								
MacroPru × *CEEC countries*	-0.011*	-0.003	-0.019	-0.019**								
	(0.002)	(0.002)	(0.003)	(0.003)								
MacroPru *Period 2000-2007*					-0.016	0.014	-0.004	0.013				
					(0.003)	(0.003)	(0.003)	(0.005)				
MacroPru × Crisis *Period 2008-2010*					0.004	0.003	0.008	-0.006				
					(0.002)	(0.002)	(0.003)	(0.004)				
MacroPru × Postcrisis *period 2010-2017*					-0.003	-0.010	-0.015	-0.028**				
					(0.002)	(0.003)	(0.003)	(0.004)				
MacroPru tightening									-0.023***	-0.003	-0.027***	-0.022***
									(0.001)	(0.001)	(0.001)	(0.002)
MacroPru Loosening									0.012**	-0.010	0.001	0.013
									(0.001)	(0.002)	(0.002)	(0.003)
R^2 (within)	0.781	0.630	0.681	0.637	0.780	0.630	0.681	0.637	0.780	0.629	0.681	0.637
Obs	15686											
banks	113											
Sample period	2000-2017											
Time fixed effects	Yes											
Bank variables	Yes											
Macro variables	Yes											

Table 11: Robustness check in which the baseline model is estimated using different dummies/indices reflecting different geographical regions, time periods and different types of policy tools (loosening or tightening). Time fixed effects are also included in the model. The coefficients on the macroprudential index and the subcategories represent the *long-run* coefficients as measured in equation 1 by $\frac{\theta}{1-\lambda}$. Standard errors are the Driscoll Kraay standard errors which are robust to general forms of cross-sectional and temporal dependence when the time dimension becomes large. Control variables are omitted from the regression table to save space. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

also includes deactivations, which are given a weight of +1 in this exercise. The results are summarised in the last 4 columns of table 11. As found in the previous regressions, macroprudential tightenings are associated with a decrease in the individual risk component of banks while the impact on the systemic linkage component is limited. Policy loosenings, however, are followed by an increase in the individual risk component. The systemic linkage component is not significantly impacted by policy loosenings.

6. Conclusion

In this paper we investigate the impact of macroprudential policy announcements on bank systemic risk measures in Europe between 2000 and 2017 and we disentangle the transmission channels through which different macroprudential policy tools may affect financial stability. We construct a macroprudential index to capture the macroprudential policy stance in a country and we subdivide the aggregate index into subindices according to the objectives of different types of tools and their design. We use the macroprudential index and its subindices to explore how bank systemic risk is affected by macroprudential policy. We use a dynamic panel framework to assess the impact of macroprudential tools on bank systemic risk both in the short run and the long run using stock market indicators of bank risk. We decompose the systemic risk measure in an individual bank risk component and a systemic linkage component. Finally, we analyse whether the transmission of macroprudential policy differs across different bank business models.

We find that, on average, the announcement of macroprudential policy actions have a downward effect on bank systemic risk. Whereas previous studies have documented a moderating effect of macroprudential measures on bank lending and real estate prices, we confirm that macroprudential policy is also effective in containing bank systemic risk, as assessed by stock market investors. This is an important finding because lowering systemic bank risk remains the ultimate objective of macroprudential policies. The strongest effect on bank risk is found for the targeted, legally binding tools that are associated with sanctions in case of non-compliance. A second conclusion is that different types of macroprudential tools in general achieve their designated objectives. We find that borrower-oriented tools and exposure limits primarily have a beneficial impact on the individual risk component of banks. Liquidity tools and measures to increase the resilience of banks are also found to lower the systemic linkage component of bank risk, hence these tools appear to be effective in targeting industry-wide risk dynamics. However, our results reveal the presence of risk-shifting behavior by banks confronted with binding macroprudential measures. While macroprudential announcements are associated with a downward effect of systemic risk, the risk reduction is primarily due to a decrease of the individual bank risk component, not the systemic linkage component. Worse, credit growth measures and exposure limits are associated with an increase of the systemic linkage component for some banks. In trying to comply with the rules, these banks may engage in riskier activities or shift to holding similar exposures, which increases the interconnectedness of the banking system.

We also investigate heterogeneous effects of macroprudential measures across different types of banks. We therefore interact the macroprudential index with business model factors that reflect the retail orientation, the income diversification and the loan quality of the bank. We find that credit growth tools and exposure limits are found to exhibit the most pronounced downward effect for retail-oriented banks. However, for retail banks we also observe an increase in their perceived systemic linkage risk, which we attribute to risk-shifting behavior. Since lending-oriented tools force these banks to lower their exposures to certain types of counterparties or to disinvest certain types of loans or securities, these banks may shift their asset composition towards exposures that make them more vulnerable to business cycle or financial market shocks. In terms of policy, our results call for a careful calibration of lending-oriented macroprudential restrictions in order to avoid the negative consequences of risk-shifting behavior. For diversified banks, credit growth restrictions are associated with higher individual risk, because they may be forced to rely even more on potentially volatile sources of non-interest income. Similarly, liquidity tools increase the systemic linkage risk of diversified banks because these restrictions force them to become even more exposed to financial market shocks. Macroprudential policies appear to be most effective for distressed banks, i.e. banks with a high ratio of non-performing loans. The systemic linkage component decreases significantly more for these banks compared to their healthy counterparts, and this effect is found for all tools.

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Appendix 1: Estimating the Marginal Expected Shortfall

To estimate the MES, we first model the bivariate process of bank and market returns:

$$r_t = H_t^{\frac{1}{2}} \varepsilon_t$$

where $r_t = (r_{m,t}\ r_{i,t})'$ is the vector of market and individual bank returns at time t, $\varepsilon_t = (\varepsilon_{m,t}\ \xi_{i,t})'$ is the vector of $i.i.d.$ $(\mathbf{0}_{2\times 1}, \mathbf{I}_{2\times 2})$ shocks. H_t is the time-varying conditional covariance matrix of which $H_t^{\frac{1}{2}}$ is the lower Cholesky factor.

$$\begin{aligned} H_t &= \begin{bmatrix} \sigma_{m,t}^2 & \sigma_{i,t}\sigma_{m,t}\rho_{i,t} \\ \sigma_{i,t}\sigma_{m,t}\rho_{i,t} & \sigma_{i,t}^2 \end{bmatrix} \\ \Leftrightarrow H_t^{\frac{1}{2}} &= \begin{bmatrix} \sigma_{m,t} & 0 \\ \sigma_{i,t}\rho_{i,t} & \sigma_{i,t}\sqrt{1-\rho_{i,t}^2} \end{bmatrix} \end{aligned}$$

The returns for the individual stock are therefore described by:

$$r_{i,t} = \sigma_{i,t}\rho_{i,t}\varepsilon_{m,t} + \sigma_{i,t}\sqrt{1-\rho_{i,t}^2}\xi_{i,t}$$

The MES can be written more explicitly as a function of correlation, volatility and tail expectations:

$$\begin{aligned} MES_{i,t-1} &= E_{t-1}(r_{i,t}|r_{m,t} < C) \\ &= \sigma_{i,t}\rho_{i,t}E_{t-1}\left(\varepsilon_{m,t}|\varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right) + \sigma_{i,t}\sqrt{1-\rho_{i,t}^2}E_{t-1}\left(\xi_{i,t}|\varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right) \end{aligned}$$

The MES measures a bank's expected equity loss when the market falls below a certain threshold over a given horizon. 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. To estimate the time-varying correlations, stochastic volatilities and tail expectations we follow Brownlees and Engle (2017) and Idier et al. (2014) and describe the estimation procedure below. In essence, we need 3 components to estimate the MES: (i) the volatility, (ii) the correlation and (iii) the tail expectations.

(i) Estimation of univariate conditional variances

Estimation of $\sigma_{i,t}$ and $\sigma_{m,t}$ can be based on any volatility model. Idier et al. (2014) use an asymmetric GARCH specification:

$$\begin{aligned} \sigma_{m,t}^2 &= \omega_m + \alpha_m r_{m,t-1}^2 + \gamma_m r_{m,t-1}^2 \mathbf{I}_{m,t-1} + \beta_m \sigma_{m,t-1}^2 \\ \sigma_{i,t}^2 &= \omega_i + \alpha_i r_{i,t-1}^2 + \gamma_i r_{i,t-1}^2 \mathbf{I}_{(i,t-1)} + \beta_i \sigma_{i,t-1}^2 \end{aligned}$$

where $\mathbf{I}_{m,t} = 1_{r_{m,t<0}}$ and $\mathbf{I}_{i,t} = 1_{r_{i,t<0}}$. It is thus assumed that volatility tends to increase more with negative shocks than positive ones.

(ii) Estimation of dynamic conditional correlation

In this step the dynamic correlation is modeled using a dynamic conditional correlation (DCC) model. The DCC model can be written as:

$$\begin{bmatrix} r_{m,t} \\ r_{i,t} \end{bmatrix} = H_t^{\frac{1}{2}} \begin{bmatrix} \varepsilon_{m,t} \\ \varepsilon_{i,t} \end{bmatrix}$$

$$H_t = D_t^{\frac{1}{2}} R_t D_t^{\frac{1}{2}}$$

$$D_t = \begin{bmatrix} \sigma_{m,t}^2 & 0 \\ 0 & \sigma_{i,t}^2 \end{bmatrix}$$

$$R_t = \begin{bmatrix} 1 & \rho_{i,t} \\ \rho_{i,t} & 1 \end{bmatrix}$$

H_t is the time-varying conditional covariance matrix and D_t is estimated separately using univariate equations. The parameter of interest R_t is modeled using an intermediate form Q_t to assure that the resulting matrix is indeed a correlation matrix (i.e. diagonal elements equal to one and all other elements lower than or equal to one in absolute value). The equation for Q_t is given by:

$$Q_t = (1 - \lambda_1 - \lambda_2)\bar{R} + \lambda_1 \varepsilon_{t-1} \varepsilon_{t-1}^{'} + \lambda_2 Q_{t-1}$$

where $\bar{R}$ is the unconditional covariance matrix of the standardized residuals. For Q_t to be stationary and positive definite some conditions must be satisfied:

$$\lambda_1 \geq 0$$
$$\lambda_2 \geq 0$$
$$\lambda_1 + \lambda_2 < 1$$

Given that Q_t is not necessarily a correlation matrix, it is transformed in the following way:

$$R_t = {Q_t^*}^{-\frac{1}{2}} Q_t {Q_t^*}^{-\frac{1}{2}}$$

where Q_t^* is a diagonal matrix with the elements of Q_t on its diagonal.

The DCC model used for the MES is slightly modified and introduces asymmetry in its specification following Cappiello et al. (2006). In the asymmetric version of the DCC model two terms are added to control for the asymmetric impact of news:

$$Q_t = (1 - \lambda_1 - \lambda_2)\bar{R} - gN + \lambda_1 \varepsilon_{t-1} \varepsilon_{t-1}^{'} + g \nu_{t-1} \nu_{t-1}^{'} + \lambda_2 Q_{t-1}$$

where $\nu_t = \varepsilon_t \mathbf{1}_{(\varepsilon_t < 0)}$ and $N = (1/T) \sum_{t=1}^{T} \nu_t \nu_t^{'}$. The conditions to ensure positive definiteness of Q_t are very similar:

$$\lambda_1 \geq 0$$
$$\lambda_2 \geq 0$$
$$g \geq 0$$
$$\lambda_1 + \lambda_2 + \delta g < 1$$

where δ is the maximum eigenvalue of $S^{-\frac{1}{2}}NS^{-\frac{1}{2}}$.

(iii) Tail expectations

Using the results from step (i) and (ii), we can calculate $\varepsilon_{m,t}$ and $\xi_{i,t}$:

$$\epsilon_{m,t} = \frac{r_{m,t}}{\sigma_{m,t}}$$

$$\xi_{i,t} = \frac{r_{i,t} - \sigma_{i,t}\rho_{i,t}\varepsilon_{m,t}}{\sigma_{i,t}\sqrt{1-\rho_{i,t}^2}}$$

from which we can then estimate the following tail expectations:

$$E_{t-1}\left(\xi_{i,t}|\varepsilon_{m,t} < c\right) \; and \; E_{t-1}\left(\varepsilon_{m,t}|\varepsilon_{m,t} < c\right)$$

where $c = \frac{C}{\sigma_{m,t}}$. Using a simple conditional average could result in unstable estimators when c is large in absolute value, since the conditioning event is only observed in a small number of instances. Brownlees and Engle (2017) instead propose a kernel estimation approach. It starts from the following relationships:

$$E_{t-1}(\varepsilon_{m,t}|\varepsilon_{m,t} < c) = \int_{-\infty}^{c} \varepsilon_{m,t} f(u|u < c)du$$

$$f(u|u < c) = \frac{f(u)}{Pr(u < c)} = \frac{f(u)}{F(c)}$$

The density function can be estimated using the kernel estimator:

$$\begin{aligned}
\hat{f}(u) &= \frac{1}{Th}\sum_{t=1}^{T}\phi\left(\frac{u-\varepsilon_{m,t}}{h}\right)\\
Pr(u < c) &= \int_{-\infty}^{c}\hat{f}(u)du\\
&= \frac{1}{Th}\sum_{t=1}^{T}\int_{-\infty}^{c}\phi\left(\frac{u-\varepsilon_{m,t}}{h}\right)du\\
&= \frac{1}{T}\sum_{t=1}^{T}\Phi\left(\frac{c-\varepsilon_{m,t}}{h}\right)
\end{aligned}$$

where h is an appropriately chosen bandwidth (usually $1.06\hat{\sigma}T^{-0.2}$) and $\Phi(.)$ is the Gaussian kernel function. This solution then leads to:

$$E_{t-1}(\varepsilon_{m,t}|\varepsilon_{m,t} < c) = \frac{\sum_{j=1}^{t-1}\varepsilon_{mj}\Phi\left(\frac{c-\varepsilon_{mj}}{h}\right)}{\sum_{j=1}^{t-1}\Phi\left(\frac{c-\varepsilon_{mj}}{h}\right)}$$

$$E_{t-1}(\xi_{i,t}|\varepsilon_{m,t} < c) = \frac{\sum_{j=1}^{t-1}\xi_{ij}\Phi\left(\frac{c-\varepsilon_{mj}}{h}\right)}{\sum_{j=1}^{t-1}\Phi\left(\frac{c-\varepsilon_{mj}}{h}\right)}$$

Appendix 2: Sample of banks

Country	Bank name	Country	Bank name
Austria	Raiffeisen Bank International	*Greece*	Bank of Attica
	Erste Group Bank		National Bank of Greece
Belgium	KBC		Piraeus Bank
	Dexia		Alpha Bank
Bulgaria	Central Cooperative Bank		Eurobank Ergasias
	First Investment Bank	*Hungary*	OTP Bank
Cyprus	Bank of Cyprus	*Ireland*	Bank of Ireland
	Hellenic Bank		Permanent Tsb
Czech Republic	Komercni Banka		Allied Irish Banks
Germany	UmweltBank	*Italy*	Banca Popolare di Milano
	MLP		Banca Piccolo Credito Valtellinese
	Deutsche Postbank		Banca Popolare dell'Emilia Romagna
	Wustenrot & Wurttembergische		Intesa Sanpaolo
	Merkur-Bank		Banca Intermobiliare di Investimenti e Gestioni
	Aareal Bank		Banca Popolare di Sondrio
	Deutsche Bank		Banco di Sardegna
	Commerzbank		Banca Popolare di Spoleto
Denmark	Nordfyns Bank		Banco di Desio e della Brianza
	Oestjydsk Bank		Credito Emiliano
	Bank of Greenland-Gronlandsbanken		Unione di Banche Italiane
	Kreditbanken		UniCredit
	Danske Bank		Banca Popolare dell'Etruria e del Lazio
	Skjern Bank		Banca Mediolanum
	Vestjysk Bank		Banco Popolare
	Jyske Bank		Banca Monte dei Paschi di Siena
	Sydbank		Banca Carige
	Lollands Bank	*Malta*	Bank of Valletta
	Ringkjoebing Landbobank		FIMBank
	Nordjyske Bank		HSBC Bank Malta
	Spar Nord Bank	*The Netherlands*	Van Lanschot
	Jutlander Bank		ABN AMRO
	Totalbanken		ING
	Moens Bank	*Poland*	Alior Bank
	Djurslands Bank		Bank BGZ BNP Paribas
	Danske Andelskassers Bank		Bank Handlowy w Warszawie
Spain	Banco Bilbao Vizcaya Argentaria		Bank Millennium
	Bankia		Bank Ochrony Srodowiska
	Bankinter		Bank BPH
	Banco Popular Espanol		mBank
	Banco de Sababell		ING Bank Slaski
	Banco Santander		Bank Zachodni WBK
	Caixabank		Getin Noble Bank
	Unicaja Banco		Bank Polska Kasa Opieki
	Liberbank		Powszechna Kasa Oszczednosci Bank Polski
Estonia	AS LHV	*Portugal*	Banco Comercial Portugues
Finland	Aktia Bank		Banco Espirito Santo
France	Société Générale		Banco BPI
	BNP Paribas	*Romania*	Banca Comerciala Carpatica
	Crédit Agricole		BRD-Groupe Societe Generale
	Crédit Industriel et Commercial		Banca Transilvania
United Kingdom	Standard Chartered	*Sweden*	Skandinaviska Enskilda Banken
	HSBC		Swedbank
	Close Brothers		Nordea Bank
	Arbuthnot Banking		Svenska Handelsbanken
	Lloyds Banking Group		
	Barclays		
	Royal Bank of Scotland		
	Cybg		
	Virgin Money Holdings		

Sample of banks