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The interaction effect of macroprudential policy and monetary policy on bank risk in the Euro Area (2006-2019)

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Abstract: This paper estimates the effect of the interaction between monetary policy and macroprudential policy on individual bank risk and systemic risk in the Euro Area from 2006 until 2018. A panel OLS regression model with monetary policy surprises as measure for the monetary policy stance is employed to exogenously identify the interaction effect. Controlling for bank-specific and country-specific characteristics, the findings show that macroprudential and monetary policy counteract each other in mitigating bank risk. This finding is robust for individual bank risk and applies mainly to capital-based macroprudential policy tools and for banks from Euro Area core countries. The results call for more intense cooperation and coordination of policy implementation.

Keywords: macroprudential policy, monetary policy, bank risk

1. Introduction

The Great Financial Crisis (GFC) of 2007-2008 provided evidence that risk and contagion in the financial sector had been greatly underestimated. Furthermore, there exists a general consensus that the flaws which were exposed during the GFC also had damaging effects in the real economy (e.g. Loutskina and Strahan, 2009; Chodorow-Reich, 2014). Therefore, since the aftermath of the GFC, financial regulators rely more and more heavily on macroprudential policy tools in order to ensure financial stability. Also, the GFC stimulated a rethinking of what role monetary policy did play and should play in affecting financial stability. In particular, a number of studies argue that the easing of monetary policy prior to the GFC had damaged financial stability by stimulating excessive risk-taking by banks (e.g. Gambacorta, 2009; Dell'Ariccia and Marquez, 2013). These studies also laid the foundation for research on the optimal combination of macroprudential and monetary policy in affecting credit supply, bank risk-taking and financial stability. This is a critical field of research, as both monetary policy and macroprudential policy measures are commonly employed in conjunction (Praet, 2018). However, due to the short history of many macroprudential policy tools, its relation with monetary policy and the impact on financial stability has not yet been thoroughly analysed. Furthermore, the related papers that exist do not provide unanimous evidence. One strand of literature argues that macroprudential policy can facilitate monetary policy transmission by targeting bank risk (e.g. Angelini et al., 2014; Brunnermeier and Sannikov, 2016). Another strand of literature argues that the two policies can have counteractive effects on the risk-taking behaviour of banks and financial stability (e.g. Woodford, 2012; Frait et al., 2011b).

This paper aims to put an end to the inconclusiveness in the existing literature. It analyses how macroprudential policy and monetary policy interact in the transmission on bank risk in the Euro Area (EA). The EA forms a solid ground for this analysis as monetary policy is common across all member states, macroprudential policy tools vary in variety and severity for each member state, and both policies vary over time. This degree of variation can be exploited to measure the interaction effect between the two policies. This paper contributes to the existing literature in three ways. Firstly, the related literature which study the interaction between macroprudential and monetary policy mainly focus on its transmission on credit (e.g. Takáts and Temesvary, 2021). However, this field of study is not enough. The GFC proved that risky and undercapitalized financial institutions do not only form a risk to themselves, but to the financial system and the real economy. In particular, when a large financial firm is undercapitalized and highly interlinked with the financial system, a negative shock to the economy cannot only trigger financial distress of the individual firm, but also the entire financial sector, as obligations spread and lending opportunities become limited. Therefore, this paper explores the transmission on both individual bank risk and systemic bank risk. Secondly, as macroprudential policy is commonly employed in conjunction with (un)conventional monetary policy, identification is difficult due to endogeneity concerns (Takáts and Temesvary, 2020; Altavila et al., 2020). To solve this, this paper employs the methodology of Altavila et al., (2020), which uses a principal component analysis on intra-day changes in the risk-free rate at various maturities around policy announcements. This measure captures the surprise element of monetary policy which ensures its exogeneity. Thirdly, this paper uses an index created by Meuleman and Van der Vennet (2020), which is constructed by tracking the lifecycle of individual macroprudential policy measures in order to generate a more sophisticated measure for macroprudential policy compared to the traditional indices. This takes into account both the scale and the scope of individual measures. This paper further extends this index for subcategories of macroprudential policy.

Overall, the results point to positive significant interaction effect between macroprudential policy and monetary policy on bank risk, and this effect is more pronounced for individual bank risk and for capital-based macroprudential policy measures. This means that macroprudential and monetary policy counteract each other in reducing individual bank risk. Furthermore, this results varies strongly between the different subcategories of macroprudential policy. Also, bank size and the degree of bank leverage suggest to play a role in the size of the interaction effect. Further robustness checks show the policy cycle is an important factor in the transmission, and that EA core countries are mainly responsible for the result. The key policy recommendations which the results bring forward are that financial regulators should aim for more coordination between the two policies, both between EA countries and on an EA level. As the result is heterogeneous across macroprudential policy tools and bank specifics, the coordination should be tailored in such a way that its detrimental effect on bank risk is minimized.

The remainder of the paper is organised as follows. Section two discusses the related literature and develops the hypotheses. Section three elaborates on the methodology and data. Section four presents the results, and section 5 concludes.

2. Literature review

This section discusses the relevant literature which is related to this study. It starts with the discussion of the relationship between macroprudential policy tools and bank risk. This is followed by a discussion of the relationship between monetary policy and bank risk. The final part elaborates on the interaction between the two policies and its effect on bank risk, and consequently develops a number of hypotheses.

2.1 Macroprudential policy and bank risk

A first strand of literature points out the need for macroprudential policy to contain financial booms in order to sustain financial stability. The "financial accelerator" is a well-known example of how financial booms could endanger financial stability. This mechanism operates through the amplification of small shocks in the real economy through increased assets prices, improving balance sheets and loosening financing conditions of (non-)financial firms, which in turn increases outstanding credit (Bernanke; 1999). This could create a high share of vulnerable (credit-impaired) firms in the economy. Another example of the dangers of financial booms is the model proposed by Adrian and Shin (2010, 2014). A positive shock to a bank's assets could incentivise the bank to take on more leverage, which makes the bank vulnerable to future negative shocks through balance sheet mismatches. Evidence shows that macroprudential policy tools are generally effective in curbing credit growth. Lim et al. (2011) study the effectiveness of a battery of macroprudential policy tools in sustaining credit growth, leverage and capital flows. The paper uses IMF survey data from 49 countries globally for the period 2000 until 2010. The findings show that many of the macroprudential policy tools under study are effective in sustaining (the procyclical component of) credit growth. Cerutti et al. (2017) use similar data in combination with Global Macroprudential policy Instruments (GMPI) for 118 countries from 2000 until 2013 and find similar evidence. Akince and Olmstead-Rumsey (2018) use a combination of IMF survey data and BIS data in a dynamic panel data model, and find that a tightening of the macroprudential policy environment is related to lower credit growth.

Although evidence shows that macroprudential policy tools are effective in curbing credit, the GFC has shown that a negative shock to a small number of financial institutions can be strongly amplified by and across the financial sector, and that the insolvency of a single (large) financial institution can endanger the solvency of the entire financial system (systemic risk). Therefore, macroprudential policy tools should target the bank balance sheet in order to increase bank resilience and the ability for banks to absorb losses. In this respect, three broad categories of macroprudential policy tools can be identified, which aim to secure financial stability by targeting different aspects of the bank balance sheet.

The first are capital-based macroprudential policy tools. Such tools enforce banks to accumulate capital in good times, that can be used in bad times to absorb any incurred losses. This enhances a bank's resilience to shocks, and can also sustain cyclical credit growth. An example of this is the amount of capital a bank must hold as a percentage of its risk weighted assets, as stated in the Basel accords. Additionally, counter-cyclical capital buffers and dynamic provisioning rules are used to increase the required capital buffers when cyclical risks build up, and release such buffers when such risks materialize. Empirical evidence support the effectiveness of such tools. Gauthies et al. (2012) find that capital requirements decrease the probability default of an individual bank. Furthermore, the findings show that capital requirements decrease the probability of a systemic crisis by up to 25 percent. Bluhm and Krahnen (2014) find similar evidence. The paper uses a metric of Value at Risk (VaR) for a system of interconnected financial institutions, and find that an increase in capital requirements can lower systemic risk as well as an individual financial institution's contribution to systemic risk. Ultimately, Andries et al. (2017) study a panel of 95 banks from North America and Europe for the period from 2008 and 2014 and show that the tightening of general capital requirements, sector-specific capital requirements and countercyclical capital buffers reduce individual bank risk-taking, as well as a bank's contribution to systemic risk[1].

A second class of macroprudential policy are liquidity-based tools. Such tools have the aim for banks to hold more liquid assets as a percentage of total assets. A major example are reserve requirements that a bank should meet. Furthermore, there exist rules which aim to increase the long term funding of a bank. An example of such a tool are limits on maturity mismatches. In sum, the goal of liquidity-based tools is to increase bank resilience against (unforeseen) liquidity shocks. The existing literature provides mixed results with respect to the effectiveness of liquidity-based tools. Furthermore, evidence of liquidity-based macroprudential policy measures on bank stability is limited to systemic risk measures only. Lim et al. (2011) show that limits on maturity mismatches have a negative impact on the credit deposit ratio of banks, having a positive effect on a bank's health through increasing resilience against liquidity shocks. Schuler and Corrado (2016) use a DSGE model, and show that liquidity-based measures, such as the liquidity coverage ratio and the net stable funding ratio, can reduce the probability of a systemic banking crisis though limiting a breakdown of

[1] The paper employs Conditional Value at Risk (CoVaR) and Marginal Expected Shortfall (MES) as measures for systemic risk. A bank's Distance to Default (DD) is used as a measure of individual bank risk-taking.

interbank lending. As a breakdown in interbank lending can jeopardise a bank's (short-term) solvency, liquidity-based measures contribute to bank resilience in times of distress. Furthermore, Adrian and Boyarchenko (2018) find that liquidity-based measures, such as the liquidity coverage ratio, can reduce general distress in the financial sector.

The third category of macroprudential policy tools are borrower-based measures. Such tools have the aim to increase a bank's resilience by reducing the credit risk on a bank's loan portfolio. One example of a borrower-based tool are limits on Loan-to-Value (LTV), which limits the loan size as a fraction of the underlying (property) value. Additionally, limits on Debt Service to income (DSTI) ratio's reduces the amount of debt a household or firm can take on relative to its income. A number of papers find evidence that borrower-based tools, especially those discussed earlier, are effective in increasing bank resilience. Andries et al. (2017) find that DTSI ratio measures are effective in reducing a bank's contribution to systemic risk and individual bank risk-taking. Ely et al. (2021) study a large global sample of banks, and find that both LTV and DTSI ratios have a positive effect on bank stability. As a measure for bank stability, the paper employs the Z-score measure, which is a proxy for bank solvency. However, there is also evidence that borrower-based tools increase the degree of risk-taking by banks. Acharya et al. (2017) find that the introduction of LTV and Loan-to-Income (LTI) ratios for residential mortgages by the Bank of Ireland in 2015 have led to an increase in risk-taking by Irish banks. The findings show that the banks in the sample increase their lending to risky firms and also increased the share of risky securities in their holding portfolios.

2.2 Monetary policy and bank risk

Although the price stability objective of monetary policy (in the EA) is conceptually different from the financial stability objective of macroprudential policy, the literature points out that there does exist a relationship between monetary policy, financial stability and bank risk. In particular, a variety of papers argue for monetary policy as one of the main factors driving excessive risk-taking by banks, especially prior to the GFC (e.g. Taylor, 2010). The "bank risk-taking channel" has been brought to light as a new transmission channel of monetary policy (Borio and Zhu, 2012). The key insight of this channel is that low interest rates which persisted for (too) long leaded to an increase in risk-taking by banks. The literature sets out two mechanisms on how the bank risk-taking channel operates. The first mechanism relates to the "search for yields". In periods when interest rates are low, low return on investments can incentivise banks to take more risk in order to, for example, meet their target. Secondly, as low interest rates have a positive effect on investment and cash flow valuations, this can in turn incentivise banks to take on more risk.

Much literature that exists today finds evidence which is in line with the bank risk-taking channel. Jiménez et al. (2012) investigate the link between the monetary policy stance and the riskiness of the loan portfolios of Spanish banks. The findings show that in the medium term, Spanish banks tend to issue more and riskier loans in general as a result of higher collateral values and "seeking for yield" caused by low interest rates[2]. Altunbas et al. (2010) study the relationship between the monetary policy stance and expected default frequencies (EDF) for 600 European and US banks in the period 1999-2008. The paper finds evidence for a link between persistent low policy interest rates and increased bank risk-taking. The relevance of the findings is substantial, as the banks in the dataset provide more than two third of total lending in the US and the EU. More recently, Dajcman (2017) estimate the link between bank risk aversion and the monetary policy rate for 11 Euro Area countries. Using a variable based on a bank's risk aversion towards its business loan activity, the paper shows that bank risk aversion increased substantially in the second half of 2007, and decreased after the second quarter in 2011. Using a monetary policy VAR, the results show that a shock in monetary policy significantly affects risk aversion of banks in the same direction, implicating that the bank risk-taking channel in the Euro Area does exist.

Although the literature provides strong evidence for a relationship between the bank risk-taking channel of monetary policy, the scope of most studies limits on the monetary policy rate as a measure for the monetary policy stance. However, starting from 2012, the ECB and central banks of other European countries moved their key policy rates below zero, giving rise to unconventional measures of monetary policy. Theoretically, the effect of unconventional monetary policy on bank risk-taking is similar as conventional monetary policy. Lambert and Ueda (2014) point out that, in line with the bank risk-taking channel, banks are further incentivised to reallocate their portfolio towards riskier assets providing higher returns once the policy rates drop below zero. Reinforcingly, quantitative easing policies supporting asset prices can have positive valuation effects.

Brana et al. (2019) study the effect of both conventional and unconventional monetary policy on bank risk for the period of 2000 until 2015. Firstly, in order to capture the monetary policy

[2] In the short term, the paper finds that low policy interest rates reduce the probability of *outstanding variable rate loans*. However, this is the result of a reduction in the interest rate burden of borrowers.

stance at the zero lower bound, the authors use the "shadow rate " in order to quantify an interest-rate-equivalent. Secondly, the central bank's total assets serve as a proxy in order to capture the effect of quantitative easing measures. To proxy bank risk-taking, the authors used the distance to default (DD) and the Z-score as dependent variables[3]. Using a dynamic panel model, the paper finds evidence for the bank risk-taking channel with respect to both conventional and unconventional monetary policy. However, the relationship between bank risk-taking and the unconventional monetary policy variables is stronger. This evidence, however, is not unanimously. Matthys et al. (2021) find no evidence for the bank risk-taking channel of unconventional monetary policy in the US for the period 2008-2015.

Additionally, a number of papers shift to the search for a relationship between monetary policy and systemic risk. Deev and Hodula (2016) study the effect of the monetary policy rate and quantitative easing on systemic risk of banks in the Eurozone in the period of 2000 until 2015. As a measure of systemic risk, the paper relies SRISK. The findings of a Vector Auto Regression (VAR) model shows that both a lowering of the policy rate and an increase in quantitative easing resulted in an increase of systemic risk. Faia and Karau (2019) provide similar evidence for a sample of 29 globally systematically important banks. The paper uses a variety of metrics for systemic risk like SRISK, long-run MES and CoVar. The effect is robust using the policy rate, the shadow rate and the total size of central bank assets as a measure for monetary policy. Kabundi and De Simone (2020) provide additional evidence for the EA banking sector for both conventional and unconventional monetary policy measures. The paper uses measures for bank interconnectedness and contagion (among others, the Bank Stability Index (BSI)) as measure for systemic risk. Kapinos (2017) studies the effect of monetary policy (as measured by its surprise element) on systemic risk measures for the US banking sector. The paper does not find evidence for an effect for CoVar, SRISK and MES as measures for systemic risk.

2.3 Interaction effect, bank characteristics and hypothesis development

The literature which directly measure the interaction effect of monetary and macroprudential policy(ies) is scare, and only focusses on the effect on the volume of bank lending. However, what does come forward in the literature is that bank specific characteristics greatly influence

[3] Both DD and Z-score are two widely used measures for bank risk-taking. DD shows how far a bank is from a default event. The Z-score measures a bank's distance from insolvency.

the transmission of monetary and macroprudential policy on bank risk and its interaction. Therefore, this allows for deriving a number of hypotheses on this subject.

In general, evidence shows that the effectiveness of monetary policy is sensitive to the degree of bank capitalization. For example, Budnik & Bochmann (2017) show at the individual bank level, that the response in lending to a tightening in monetary policy is lower for well-capitalized banks. Moreover, Dell'Ariccia et al. (2016) provide evidence that the bank risk-taking channel of monetary policy is greater for better capitalized banks. This evidence is theoretically explained by the classical risk-shifting incentives of low-capitalized banks. Banks which are well capitalized therefore face a higher marginal increase in risk-taking which is attributed to an easing in monetary policy. Hence, tighter capital-based macroprudential policy is expected to decrease the effectiveness of monetary policy in curbing credit growth, and would increase the risk-taking behaviour of banks caused by monetary policy. Therefore hypothesis 1.1 states;

H1.1: The interaction effect of capital-based macroprudential and monetary policy on bank risk is positive.

Additionally, evidence shows that the degree of liquidity of a bank can also impact the effectiveness of monetary policy. Kashyap and Stein (2000) provide evidence that more liquid banks with more long-term financing respond less to changes in monetary policy. Furthermore, Lucchetta (2007) find evidence that for European banks an increase in the monetary policy rate has a positive effect on the degree of liquidity retention. From the perspective of the bank risk-taking channel of monetary policy, this would mean that the two policies potentially reinforce and counteract each other. However, since evidence of the effectiveness of liquidity-based macroprudential policy measures on bank risk only relates to the systemic part, the interaction effect of liquidity-based macroprudential policy measures and monetary policy on bank risk seems ambiguous, and this effect is only expected on systemic bank risk. Therefore, hypothesis 1.2 states;

H1.2: The interaction effect of liquidity-based macroprudential and monetary policy on bank systemic risk is positive.

Compared to the latter, the category of borrower-based macroprudential policy measures is the least frequently investigated in conjunction with monetary policy. However, one paper focuses on the loan-to-value measure specifically. Maddaloni and Peydró (2013) analyse how loan-to-value measures in the EA affect the transmission of monetary policy. The paper provides suggestive evidence that more stringent loan-to-value measures reduce excessive risk-taking by banks more in a low interest rate environment. This suggests that the two policies substitute each other in affecting the risk-taking of banks. Hence, it is expected that the interaction effect with respect to borrower-based macroprudential policies is insignificant. Therefore, hypothesis 1.3 states;

H1.3: The interaction effect of borrower-based macroprudential and monetary policy on bank systemic risk is insignificant.

Thus far, the impact of bank specific characteristics on the interaction effect are characterized by those that are actively targeted by macroprudential policy measures. However, a number of additional factors are frequently associated with the effectiveness of both monetary and macroprudential policy.

The size of a bank is associated with its contribution to systemic risk and the effectiveness of macroprudential policy tools and monetary policy (e.g. Laeven et al., 2016). Large financial institutions face incentives to take more risk, irrespective of the severity of macroprudential policy. Similarly, the sensitivity of monetary policy on the risk-taking behaviour of banks is smaller for large bank. One possible explanation of this phenomenon is the belief in “too big to fail”. Furthermore, Cerutti et al. (2017) provide evidence that financial institutions are incentivised to avoid macroprudential regulation after a tightening in macroprudential policy, and shift lending towards non-domestic borrowers. Similarly, Aiyar et al. (2014) find evidence that a tightening of macroprudential policy is associated with an increase in lending of foreign bank branches. Since larger banks generally have more access to international borrowers, which implies that macroprudential policy is less effective for larger banks. Additionally, Altunbas et al. (2018) find that small banks face a stronger effect on bank risk in response to changes in multiple classes op macroprudential policy tools. Hence, it is expected that larger banks are less subject to the interaction effect than smaller banks. Therefore, hypothesis 2.1 states;

H2.1: The interaction effect of macroprudential and monetary policy on bank risk is smaller for larger banks.

Another bank specific factor which is emerges frequently in the literature is the degree of leverage of a bank. Broadly, the degree of leverage of a bank is associated with a wide battery of macroprudential policy tools. First of all, capital-based tools directly put a limit on the degree of leverage by the use of capital requirements. Furthermore, Paoli and Paustian (2017) argue that liquidity requirements lower the amount of new loans that banks extend, and reduce the degree of bank leverage. Ultimately, Ely et al. (2021) show that the transmission of a wide variety of macroprudential policy measures on bank risk is sensitive to the degree of bank leverage. The findings show that overall macroprudential policy measures are more effective in reducing bank risk-taking for more levered banks. As Dell'Ariccia (2016) finds that the bank risk-taking channel of monetary policy is less profound for well-capitalized and low-levered banks, it is expected that the interaction effect is more pronounced for more levered banks, Hence, hypothesis 2.2 states;

H2.2: The interaction effect of macroprudential and monetary policy on bank risk is greater for banks with a higher degree of leverage.

Also, the degree of competition a bank faces may have an effect on the effectiveness of the transmission of macroprudential and monetary policy. Some papers argue that bank competition has an effect on the risk-taking behaviour of banks. For example, Jimenez et al. (2013) find that a higher degree of bank competition, as measured using the Lerner index, is associated with a higher degree of risk-taking. A possible explanation for this finding is that a high degree of bank competition incentive banks to maintain profitability through an increase in risk-taking. On the other hand, Anginer et al. (2014) argue that higher bank competition can increase bank stability by stimulating risk diversification. Andries et al. (2017) study the effect of a number of individual macroprudential policy tools in markets with a different degree of bank competition. The findings show that a tightening of liquidity requirements and countercyclical capital requirements are less effective in limiting bank risk-taking and a bank's contribution to systemic risk in a more competitive banking environment. Relating to the risk-taking channel of monetary policy, Shikimi (2023) finds that Japanese banks in environments with lower average market power (so a higher degree of competition) engage more in risk-taking, especially when the monetary policy rate is low. Ely et al. (2021) find that the degree of banking competition as measured by the Herfindahl-Hirschman index does influence the transmission of macroprudential policy measures and bank risk. However, the sign and the significance varies greatly between specific policy measures. Therefore, no specific hypothesis with respect to the influence of banking competition comes forward. It is nonetheless insightful to study how the degree of banking competition affects the interaction effect on bank risk, and will be included in the analysis.

3. Methodology and data

This section outlines the econometric method(s) which this paper employs. Furthermore, the main identification strategy and assumptions of the model are discussed. Also, the construction of the main variables are discussed in detail, and finally the sample selection and descriptive statistics are reported.

3.1 Methodology

3.1.1 Baseline model

To evaluate the impact of the interaction between monetary policy and macroprudential policy on bank risk in the EA, this paper departures from the basic functional form as displayed below;

$$Risk_{b,c,t} = \beta_0 + \beta_1 MP_t + \beta_2 MAP_{c,t} + \beta_3 \left(MP_t * MAP_{c,t}\right) + \varepsilon_{b,c,t} \quad (1)$$

with b = 1,…, N, c = 1,…, C, t = 1,…, T, where i is the bank, c is the country, and t is time. In baseline equation (1), *Risk* represents a measure for bank risk, *MP* represents a measure for the monetary policy stance in the EA, and *MAP* represents measure of the macroprudential policy stance in an EA country. This makes β_3 the main regression coefficient of interest, as it represents the interaction effect of *MP* and *MAP* on bank risk.

The majority of the literature which estimates models with bank risk variables and measures for monetary, macroprudential policy or both, rely in GMM techniques (e.g. Zhang et al., 2018; Ely et al., 2021) and OLS techniques (e.g. Stiroh, 2006; Igan et al., 2022) for panel datasets. Both techniques come with its advantages and disadvantages. In a variety of papers, the GMM techniques are preferred since it addresses the possible autocorrelation in bank risk measures, as well as the endogenous relationship between bank risk measures and additional bank-specific variables. Other papers prefer OLS techniques since they do not consume many time periods, and therefore do not lead to a loss of observations in order to establish the required instruments to mitigate endogeneity. This paper relies on an OLS technique, which is motivated by three reasons. Firstly, this paper employs a specific systemic bank risk measure which is only available for large banks in Europe. Therefore, the already small sample size would be decimated. Secondly, this paper employs another (individual) bank risk measure, which is available for a large number of banks. However, although the sample size with this bank risk measure allows for a GMM estimation technique, an OLS technique is preferred in order to derive comparable results as with the estimation of the model with the systemic bank risk measure. Thirdly, as the data sample includes both active and inactive banks, the use of a GMM estimation technique would reduce the available accounting years of the inactive banks to an extend that would drastically reduce their variability.

Nonetheless, it is likely to assume that macroprudential policy can be affected by monetary policy, as well as the other way around, as both policies affect and are affected by business and credit cycles. Also, both monetary policy and macroprudential policy are likely to move in the same direction, which would further bias the interaction coefficient between monetary and macroprudential policy. To address the concerns of endogeneity in the estimation of the coefficient β_3 in equation (1), this paper applies a specification which is similar to Altavilla et al. (2019). To exogenously capture the monetary policy stance in the EA, this paper identifies monetary policy shocks (surprises) based on intra-day interest rates around official ECB council decisions. Additionally, to ensure that macroprudential policy is not affected by these shocks, the *MAP* variable is lagged by one period. A detailed construction of both the *MAP* and the *MP* variable is discussed later on.

To further filter out the effect of bank characteristics on the coefficients of interest, a set of banks-specific control variables is appended to the model. These are the natural logarithm of total assets (*Size)*, the ratio of liquid assets over total assets (*Liquidity)*, the degree of leverage, as measured by total debt over equity (*Leverage*), the ratio of deposits over total assets (*Deposit Ratio*), the ratio of total loans over total assets (*Loans*), and a cost efficiency ratio, as measured by total costs over total income (*Cost Ratio*). The inclusion of these bank-specific variables is common throughout the related literature.

Finally, it is likely that the macroprudential policy stance of an EA country is endogenously related to a country's economic developments. For example, if a country experiences an economic boom, this is accompanied with tighter macroprudential policy. Similarly, an economic downturn is accompanied with looser macroprudential policy. To control for these factors and to further address this source of endogeneity, a set of country-specific variables in appended to the model. It includes the level of inflation, as measured by the Consumer Price Index (*CPI*), the real growth rate of GDP (*Real GDP Growth)*, the growth in outstanding credit (*Credit Growth)* and the Herfindahl-Hirschman-index as a measure of banking concentration (*HHI*). Additionally, interactions between monetary policy surprises and *CPI*, *Real GDP Growth* and *Credit Growth* are included to control for the asymmetric relationship of monetary policy, credit cycles and business cycles across EA countries (Altavilla et al., 2020). The country-specific control variables are also lagged by one period in order to mitigate the concerns that these are affected by the bank risk variables. Finally, to mitigate the effects of time-varying EA wide factors, time-fixed effects are appended to the model.

Equation (1) is conclusively saturated as follows;

$$Risk_{b,c,t} = \beta_0 + \beta_1 MAP_{c,t-1} + \beta_2\left(MP_t * MAP_{c,t-1}\right) + \beta_3 BC_{b,t} + \beta_4 CC_{c,t-1} + \varphi_t + \varepsilon_{b,c,t} \quad (2)$$

where $BC_{b,t}$ represents the vector of bank-specific control variables, $CC_{c,t-1}$ represents the vector of country-specific control variables, and φ_t represent the time-fixed effects parameters. The remaining variables are similar as in equation (1). Note that the MP_t is missing in equation (2), as its effect is fully absorbed by the time-fixed effects parameters (φ_t).

3.1.2 Heterogeneous effects

Previous literature has pointed towards the importance of various banks-specific, but also country-specific factors in the transmission of monetary and macroprudential policy on bank risk. Factors which come forward frequently in the literature are the size of a bank, the degree of leverage of a bank, and the degree of competition a bank experiences (e.g. Demirgüç-Kunt and Huizinga, 2010; Fazio et al., 2015; Tabak et al., 2012; Ely et al., 2021). To analyse these heterogeneous effects, three additional regressions are estimated. The model as in equation (2) is appended as follows;

$$Risk_{b,c,t} = \beta_0 + \beta_1 X_{b,c,t} + \beta_2(MP_t * X_{b,c,t}) + \beta_3(MAP_{c,t-1} * X_{b,c,t}) + \beta_4\left(MP_t * MAP_{c,t-1} * X_{b,c,t}\right) + \beta_5 BC_{b,t} + \varphi_{t,c} + \varepsilon_{b,c,t} \quad (3)$$

where $X_{b,c,t}$ represents either the size of a bank or the degree of leverage of a bank[4]. Furthermore, the variable $\varphi_{t,c}$ now represents time and country interacted fixed effects. These are included to filter out country specific time varying factors which may affect bank-specific variation[5]. The remaining variables are similar as in equation (2). Note that now the (vector of) variables MP_t , $MAP_{c,t-1}$, $MP_t * MAP_{c,t-1}$ and $CC_{c,t-1}$ are absent as the inclusion of country*time fixed effects ($\varphi_{t,c}$) makes these variables unidentifiable.

The third additional regression, which estimates the heterogeneous effect of bank competition, is presented as follows;

[4] Note that the variable which $X_{b,c,t}$ is not included in the vector $BC_{b,t}$ or $CC_{c,t-1}$ anymore, as this would result in the double entry of variables.
[5] Altavilla et al. (2021) include different sets of fixed-effects in the estimation of an interaction effect of monetary policy and macroprudential policy which is further interacted with bank specific characteristics. The model with the highers fit (highers R-squared) is the one with time*country-fixed effects.

$$Risk_{b,c,t} = \beta_0 + \beta_1 MAP_{c,t-1} + \beta_2\left(MP_t * MAP_{c,t-1}\right) + \beta_3 HHI_{c,t} + \beta_4(MP_t * HHI_{c,t}) + \beta_5(MAP_{c,t-1} * HHI_{c,t}) + \beta_6\left(MP_t * MAP_{c,t-1} * HHI_{c,t}\right) + \beta_7 BC_{b,t} + \beta_8 CC_{c,t-1} + \varphi_t + \vartheta_c + \varepsilon_{b,c,t} \quad (4)$$

where $HHI_{c,t}$ now presents the degree of bank competition in a country, as measured using the Herfindahl-Hischman-index. Furthermore, φ_t again represents time fixed effects, and ϑ_c now represents country fixed effects[6]. These vectors of fixed effects are now included separately in the model, as the interacted vector of both fixed effects would eliminate the variation in all the key variables.

3.2 Measures for bank risk

Previous literate employs a variety of variables to measure the degree of bank risk. Traditionally, these measures capture the risk of a financial institution individually, and are derived from market-based or accounting-based data[7]. However, since the onset of the GFC, the focus has shifted more towards measures of systemic risk a financial institution imposes to the financial system. To capture both aspects, this paper employs two measures for bank risk. The first is a measure of individual bank risk, the Z-score. The second is a measure of systemic bank risk, and is SRISK. The choice and specification of both measures will be elaborated in more detail.

3.2.1 Individual bank risk; Z-score

The Z-score is one of the most widely used measures of banks stability in existing literature (e.g. Laeven and Levine, 2009; Fiordelisi and Mare, 2014). The key insight of the Z-score is that it measures a bank's distance from insolvency. This measure can be considered to be an index which proxies an individual bank's financial soundness and risk. The Z-score is calculated as follows;

$$Z_{i,t} = \frac{ROA_{i,t} + CAR_{i,t}}{\sigma(ROA_{i,t})} \quad (5)$$

in which $ROA_{i,t}$ refers to the return on average assets for bank *i* in year *t*, and $CAR_{i,t}$ refers to the capital-to-asset ratio for bank *i* in year *t*. $CAR_{i,t}$ and is calculated as total equity divided by

[6] The seperate inclusion of time and country fixed effects allows again for the identification of *MAP* and *MP*MAP*.

[7] Accounting-based measures are derived from balance-sheet (book-value) data,whereas market-based measures are derived from market (market-value) data.

total assets. Finally, the denominator $\sigma(ROA_{i,t})$ is the standard deviation of the return on average assets.

Equation (5) shows that the Z-score essentially estimates how many numbers of standard deviations the return on assets has to fall below the expected value of the return on assets, before it completely exhausts the total equity of the bank. Once this happens, the bank becomes insolvent. This means that a lower value for the Z-score indicates a more risky bank. This paper follows the procedure of Beck et al. (2013) for the calculation of the standard deviation of the return on average assets. Instead of a calculation based on the entire sample, a rolling standard deviation in a window of three years is calculated. This approach comes with two advantages. Firstly, if the standard deviation is calculated over the entire sample, the within bank variation will be exclusively the result of variation in the numeration of equation (5). Secondly, not all banks have a similar amount of available accounting years. The calculation of the standard deviation of the return on average assets using a rolling window ensures that this calculation employs the data from a similar number of periods.

3.2.2 Systemic bank risk; SRISK

If a single bank faces a capital shortfall, it is dangerous for the bank itself, but it is also dangerous for the economy as a whole if many banks in the financial system face a capital shortfall. Therefore, the stability of an individual bank may ensure the stability of the financial system as well as the real economy.

The SRISK measure aims to capture this degree of systemic risk. It has been constructed and employed in the paper by Brownlees and Engle (2017) to provide a ranking of financial institutions based on their contribution to the financial crisis of 2007-2009. SRISK measures a financial firm’s capital shortfall conditional on a severe market decline. A higher value of SRISK implies that the firm forms a higher level of systemic risk to the financial sector. The reasoning behind this measure is that a financial firm is perceived to be systemically risky, if it faces a large expected capital shortfall just when the financial sector itself is in distress.

Equation (6) represents a formal description of the capital shortfall of firm *i* in period *t*.

$$CS_{i,t} = kA_{i,t} - EQ_{i,t} = k\left(D_{i,t} + EQ_{i,t}\right) - EQ_{i,t} \tag{6}$$

where *k* is the regulatory capital fraction, $A_{i,t}$ is the value of quasi-assets, $D_{i,t}$ is the book value of debt and $EQ_{i,t}$ is the market value of equity. The intuition behind equation (6) is that a positive value of $CS_{i,t}$ (and thus a capital shortfall), occurs when a firm has less available capital (as measured by $EQ_{i,t}$) than it should hold as required by the financial regulator ($kA_{i,t}$), the firm is in financial distress. Vice versa, for a negative value of $CS_{i,t}$, a firm has more capital than it should hold. Due to the available working capital, the firm is perceived to be financially healthy.

To arrive at the capital shortfall of a firm in the case of a systemic event, the conditional expectation of the capital shortfall in the case of a market decline below a certain threshold *C*, over a time horizon *h*, should be estimated. Thus, SRISK is defined as follows;

$$
\begin{aligned}
SRISK_{i,t} &= E_t\left(CS_{i,t+h} \middle| R_{m,t+1:t+h} < C\right), \\
&= kE_t\left(D_{i,t+h} \middle| R_{m,t+1:t+h} < C\right) - (1-k)E_t(EQ_{i,t+h} | R_{m,t+1:t+h} < C) \qquad (7)
\end{aligned}
$$

where $R_{m,t+1:t+h}$ is the expected multiperiod market return from *t+1* to $t{+}h$. Further is assumed that in the occurrence of a systemic event, debt cannot be renegotiated. This implies that $E_t\left(D_{i,t+h} \middle| R_{m,t+1:t+h} < C\right) = D_{i,t}$. This results in following equation;

$$SRISK_{i,t} = k * D_{i,t} - (1-k) * EQ_{i,t} * \left(1 - LRMES_{i,t}\right) \qquad (8)$$

where $LRMES_{i,t}$ is the long-run marginal expected shortfall. It is the expectation of a firm's multiperiod equity in the case of a systemic event, and can be expressed as follows;

$$LRMES_{i,t} = -E_t(R_{i,t+1:t+h} | R_{m,t+1:t+h} < C) \qquad (9)$$

where $R_{i,t+1:t+h}$ is the multiperiod firm equity return form *t+1* to $t{+}h$.

From equation (8) and (9) it can be derived that SRISK is a function of the firm's size and the level of debt, the regulatory capital ratio, and the expected devaluation of a firm's equity given a severe market decline. SRISK is higher for larger firms, highly levered firms, and firms that are sensitive to market declines. It should be mentioned that SRISK implicitly depend on the regulatory capital ratio *k*, the threshold market decline *C* and the estimation of the LRMES.

The complete methodology, including the calculation of the LRMES and SRISK, is extracted from the VLAB of Stern Business School at the New York University. For European financial firms, the computation of the LRMES is based on the dynamic conditional beta model from Engle (2016). The data is available for the largest financial firms in Europe, and is provided on a monthly frequency.

3.3 Macroprudential policy index

In the aftermath of the GFC, a large variety of macroprudential policy measures have been implemented to ensure its stability. As these measures have been introduced and implemented at a national level, there exists heterogeneity in macroprudential policies across the EA, both in scale and in scope. In order to exploit the heterogeneity and extensivity of macroprudential policies across EA countries, this paper relies on the ECB Macroprudential Policies Evaluation Database (MaPPED). This database has been constructed by experts from the ECB and national central banks of the EU28 countries, and has been introduced by Budnik and Kleibl (2018). The database provides a detailed overview of 1925 macroprudential policy actions which have been undertaken on a monthly basis between 1995 and 2017 in the 28 countries which form the European Union. Unfortunately, this database (as well as similar databases) does not provide a quantification of each policy tool or policy action that have been undertaken. This is because the target, magnitude and implementation of each individual measure differs from country to country, which hinders its comparability. However, MaPPED is preferred over similar databases like the BIS database by Boh et al. (2017) and the IMF iMaPP by Alam et al. (2019). In contrast to these other databases, MaPPED provides detailed life-cycle overviews of each policy measure. The database indicates dates on the activation of policies, the deactivation of policies, but also changes in the scope and scale of policy actions. Furthermore, each policy action is classified as a policy tightening, policy loosening, or an unknown/ambiguous effect. For the 19 EA countries, this adds-up to 442 macroprudential policy tools, which are compromised out of 1199 individual policy actions.

To exploit the information on macroprudential policy actions in this database, this paper follows the novel procedure of Meuleman and Van der Vennet (2020) in the creation of a country-level macroprudential policy index. Since there exists a large variation within the different categories of macroprudential policies, the quantification of the index is based on the changes of a particular policy over time rather than across individual policies. This is achieved by establishing a weighing scheme for each action within the same policy tool. After having assigned a weight to each policy action, this weight receives a "sign" based on whether a policy action is classified as a policy "tightening" or policy "loosening". This sign classification is labelled as "impact". Table A1 presents an overview of the weighing scheme, the impact, and the resulting final weight of a policy action. To quantify the life-cycle of each policy tool, the final weight of each policy action is cumulated over time, corresponding to the year a policy action has been implemented. When a policy tool is deactivated, the total cumulated weight drops to zero. Finally, to arrive at a country-level macroprudential policy index, for each year, the final weight of all policy actions in a particular country and year are accumulated.

It should be noted that this method treats the severity of each individual policy tool equally, which may not be the case in reality, and certain policy tool are more effective than others. Therefore, in addition to the overall macroprudential policy index, this paper extends the procedure of the creation of the total index, to three sub-indices of macroprudential policy tools. These sub-indices are capital-based, borrower-based, liquidity-based macroprudential policy instruments[8]. In Table A2 presents a detailed overview of which policy tool is assigned to which sub-category. The assignment of policy tools to a subcategory is in line with the creators of the MaPPED database (Budnik and Kleibl, 2018).

The capital-based sub-index embodies macroprudential policy tools which target the funding and loss reserves of banks. It includes measures like minimum capital requirements, capital buffers and loan loss reserves. Furthermore it includes regulatory leverage ratios, as well as caps and floors on parameters which are used to calculate (sectoral) risk weights.

The borrower-based sub-index includes macroprudential policy tools which target the payment capacity of borrowers. This is achieved by setting limits on the total loan size of a borrower, by setting limits of the maturity on loans and limiting the overall debt of borrowers. Examples of leading measures are the limits on loan-to-value ratios which aim to limit the wedge between the value of a mortgage and the value of the underlying property. Other examples are limits on debt-to-income and debt-service-to-income, which ensure that borrowers are likely to meet the repayment of interest and loans in the future.

The liquidity-based sub-index consists of macroprudential policy measures which are undertaken to ensure that is enough liquidity available in the financial system. An example of this is the liquidity-coverage-ratio, which forces banks to hold a certain amount of liquid assets in order to account for of short-term liabilities. Furthermore, asset-based reserve requirements and liability-based reserve requirements also make sure that banks are able to meet their liabilities when faced with sudden withdrawals. Also, limits on maturity mismatch make sure that banks do not excessively rely on short-term liabilities for the financing of long-term assets.

Table A3 presents the mean stance of the total MAP index, as well as the four sub-indices in

[8] A residual sub-index contaning all policies which are not assigned to either capital-, borrower-, or liquidity-based macroprudential policy measures is disregarded in final analyses. Since this residual category contains divergent policy measures which cannot be subject to interpretation.

the EA and for each individual country. The mean stance of the total MAP index in the EA is 7.343, which indicates an overall tightening MAP stance for the period 2006-2019. The majority of the MAP index consists of capital-based measures (4.647), followed by liquidity-based measures (1.95), other measures (0.681) and borrower-based measures (0.066). However, there exists large heterogeneity in the severity of the MAP stance between the EA countries. For example, the highest mean the total MAP index is in Cyprus (22.527), whereas the lowest is observed in Italy (2.68).

To give an illustration of the time dynamics of the monetary policy stance in the EA, Figure A1 presents how the mean stance of the total MAP index, and its components, have evolved over time. The period between of 2010 until 2015 is characterized by a rapid increase in the mean MAP index, mainly due to an increase in capital-based measures. Although in 2006, the majority of MAP policy measures are liquidity-based, these are rapidly overtaken by capital-based measures in 2015. Figure A2 displays how the total MAP index evolved over time for each individual country. Over the full period, each country faces an increase in the total MAP stance. However, the severity and the timing of the implementation of MAP policies varies between countries.

3.4 Monetary policy measure; the surprise element.

The ECB, as well as other central banks around the world, have a variety of policy measures available in order to sustain credit growth and to maintain financial stability. Especially since the onset of the GFC, the ECB has complemented its conventional measure of setting policy rates with a wide array of unconventional measures. Some examples of these are (un)targeted liquidity provisioning and quantitative easing. One of the main causes of the complementation of unconventional measures is that interest rates have dropped into the negative zone, the so-called zero lower bound, making conventional monetary policy ineffective (Bernanke and Reinhart, 2004). Therefore, finding a measurement of the stance of monetary policy in a single variable which captures all elements of monetary policy comes with its difficulties. Moreover, the variety of conventional and unconventional measures may affect different segments of the yield curve. For example, the conventional short-run monetary policy interest rate may affect the short-run segment of the yield curve more, whereas quantitative easing may affect the long-run segment of the yield curve more. This makes it even harder to arrive at a single policy rate.

In order to establish a comprehensive measure of the monetary policy stance of the ECB and to assure the exogeneity of this measure, this paper relies on the dataset which has been constructed by Altavilla et al. (2020). This dataset captures monetary policy surprises through changes in high-frequency intraday risk-free rates, the overnight index swap rates (OIS), around official monetary policy announcements from the 7th of January 1999 until the 16th of December 2021. The changes in these OIS's are reported for different maturities ranging from one month to ten years. In particular, for each maturity, the monetary policy surprise element has been calculated by measuring the change of each OIS from 15 minutes before a press release to 15 minutes after a press conference by the Governing Council of the ECB. As these surprise elements represent the unanticipated part of monetary policy actions, the presence of endogeneity in monetary policy is eliminated. This ensures that monetary policy actions are not driven by macroprudential policies. Finally, to establish a comprehensive measure which embodies the surprise elements for all OIS maturities, a principal component analysis (PCA) is conducted. PCA is used to combine information that is stored in many variables in a smaller set of "sub-variables". This means that based on the set of OIS's with maturities ranging from one month to ten years, the first principal component captures a linear combination of the OIS's with the highest fit, i.e. explaining the maximum variance[9]. Table A2 shows that the first principal component explains 78% of the variation in all OIS's. Therefore, this method allows to capture all aspects of monetary policy surprises in a single monetary policy surprise variable to a substantially large extend.

Figure A3 presents the sum of the surprise elements for each year of the sample period. The first years of the sample period are characterized by negative monetary policy surprises. Large negative monetary policy surprises, or monetary easing surprises, can be observed in 2009 and 2011. In 2009, the ECB seemingly surprised the markets by lowering the deposit facility rate with 175 basis points over the year. In 2011, this was the case after the announcement of the introduction of long-term refinance operations (LTROs) for the provision of liquidity to commercial banks, as well as the announcement that the ECB would engage in large scale covered bond purchases. Large positive monetary policy surprises, or monetary tightening surprises, can be observed in 2015 and 2019. In 2015 and 2019, markets expected lower policy rates and larger increases in the volume of asset purchases.

[9] For a small number of monetary policy announcement dates, not all OIS's are available. In these cases, a PCA has been conducted with the available OIS's.

3.5 Sample selection and descriptive statistics

3.5.1 Sample selection

For the extraction and creation of the bank-specific variables, this paper relies on bank balance sheet data from Bureau Van Dijk's Orbis BankFocus (2022). This data source provides a wide range of financial report data on a yearly frequency. The panel of banks includes cooperative banks, savings banks, commercial banks, real estate & mortgage financing banks and investment banks. Both active and inactive banks are included in the dataset to counter the potential survivorship bias. To avoid duplication of entry data, only the unconsolidated income statements of banks are considered. Both listed and unlisted banks are included. As the majority of European banks are unlisted, the sample forms a fair representation of the reality and provides ground for solid out of sample prediction. Furthermore, all bank-specific variables are winsorised at the 1- and 99-percentile level to exclude potential outliers. Since the Z-score variable is highly skewed, this variable is taken in the natural logarithm. However, as the natural logarithm of a negative value is undefined, unaltering the data would result in the loss of all negative Z-score values. As this would results in non-random elimination of data (since the "most solvent" banks would be excluded), all negative values of the Z-score are rescaled, so that these values now lie between zero and the minimum positive value of observed Z-score (Bouvatier, 2017).

The bank-level data is merged with the macroprudential policy data and EA wide monetary policy surprise data. Finally, the country-specific control variables, collected from the IMF World Economic Outlook Database and Eurostat, are appended to the sample. This results in a final sample that consists of 2668 banks, with a total number of observations of 22921, which has a yearly frequency, and covers the years from 2006 until 2019. As mentioned before, the SRISK variable is only available for the largest financial institutions in Europe. This results in the reduction of the sample size to 74 banks, with a total of 656 observations, covering the years from 2006 until 2019.

In Table 1 the summary statistics of the variables used in the analysis are displayed. All variables in levels are in US dollars. Table 2 presents similar statistics, but only for the banks of which the SRISK measure is available.

Table 1 shows that the mean value of the log of the Z-score is 1.87, and the mean size of a bank (also in log) is 13.424. Furthermore, Table 2 shows that the mean log of SRISK is 6.028. As expected, the mean size of a bank for which the SRISK measure is available is substantially larger, with a value of 17.292. For the remaining bank specific variables, only the degree of leverage is substantially different in the SRISK sample. The mean degree of leverage for a bank in the SRISK sample is 3.619, which is more two times the degree of leverage of a an average bank in the full sample.

For a fair comparison, Table A5 presents key summary statistics for each country for the full sample. Countries with the most significant number of banks in the full sample are Germany, Austria and Italy. On the other hand, Greece, France and The Netherlands provide on average the largest banks in the full sample. Throughout the sample period, the mean (log of) Z-score is the highest in Germany, Spain and Finland, implying that on average, banks in these countries are the furthest away from bankruptcy form 2006 until 2019. Similar statistics for the SRISK sample are displayed in Table A6. Note that Estonia, Latvia, Luxembourg and Slovenia are absent as the SRISK measure is not available for banks from these countries. The most significant number of banks in the SRISK sample are from Italy and France. In terms of size, Spain stands out for having on average the largest banks. On average, banks from Belgium, Germany and The Netherlands have the largest degree of (log) SRISK.

Figure A4 gives an illustration of the evolution of both bank risk measures over time. Note that left vertical axis presents the mean of the log Z-score over the full sample for each year. The left had axis presents the total amount of outstanding SRISK (in logs), for the SRISK sample. This gives a rough indication of the total capital shortfall that the large banks in the sample contribute to the financial system.

Table 1: Descriptive statistics; full sample.

Variable	Obs	Mean	Std. Dev.	Min	Max
Ln(Z-score)	22921	1.87	1.469	-6.596	9.278
Ln(Size)	22921	13.424	1.889	8.931	18.716
Loan/Assets	22462	.582	.194	.004	.978
Liquid ratio	22882	.233	.196	.008	.977
Deposit Ratio	22124	.701	.193	.002	.931
Leverage	14020	1.536	5.313	0	44.457
Cost Ratio	22865	70.943	18.139	5.128	178.681
MAP total	22921	7.343	3.776	.1	29.579
MAP capital	22921	4.647	3.028	-.45	11.329
MAP borrower	22921	.066	.442	-1.25	3.917
MAP liquidity	22921	1.95	1.137	-.15	8.15
MAP other	22921	0.656	1.519	-1	13.75
MP Surprise	22921	-.084	4.212	-9.282	6.444
CPI	22921	1.404	.887	-1.7	5.7
Real GDP Growth	22921	1.517	1.785	-8.1	25.2
HHI	22921	.047	.041	.018	.388
Credit Growth	22921	-.01	.034	-.341	.279

Note: This table presents descriptive statistics for the 2668 sample banks, including the 19 EA countries. The balance sheets are annual and comprise the period from 2006 to 2019, and all monetary amounts are in US dollars.

Table 2 Descriptive statistics; SRISK sample.

Variable	Obs	Mean	Std. Dev.	Min	Max
Ln(SRISK)	656	6.028	3.465	-.395	11.919
Ln(Size)	656	17.292	1.275	11.979	18.716
Loan/Assets	617	.547	.231	.004	.978
Liquid ratio	633	.284	.203	.008	.977
Deposit Ratio	605	.446	.217	.002	.931
Leverage	638	3.619	5.604	0	44.457
Cost Ratio	624	64.246	26.196	5.128	178.681
MAP total	656	7.233	5.534	.1	29.579
MAP capital	656	3.89	2.402	0	11.329
MAP borrower	656	.219	.771	-1.25	3.75
MAP liquidity	656	1.626	1.842	-.15	8.15
MAP other	656	1.482	3.224	-1	13.75
MP Surprise	656	-.099	4.28	-9.282	6.444
CPI	656	1.205	1.021	-1.5	3.7
Real GDP Growth	656	1.248	2.565	-10.1	25.2
HHI	656	.084	.066	.018	.388
Credit Growth	647	-.019	.044	-.341	.084

Note: This table presents descriptive statistics for the 74 sample banks, including the 19 EA countries. The balance sheets are annual and comprise the period from 2006 to 2019, and all monetary amounts are in US dollars.

4. Results

This section discusses the main results of the analysis. Firstly, the baseline results as estimated in equation (2) are presented. Secondly, this section analyses the heterogenous factors; (1) the size of a bank; (2) the degree of leverage of a bank; (3) the degree of competition a bank faces. Finally, a number of robustness checks are conducted.

4.1 Baseline results

Table 3 presents the results of the baseline regression of equation (2). The first four columns presents the results with the natural logarithm of the Z-score. The last four columns present the results with the natural logarithm of SRISK as dependent variable. Note that an increase (decrease) in bank risk is associated with a decrease (increase) in the Z-score, and an increase (decrease) in SRISK. Furthermore, in each column, the variable MAP corresponds to the (sub)index as indicated above that column.

Column (1) to (4) show that the significant β_1 coefficients all have a negative impact on individual bank risk, as displayed with a positive impact the Z-score. This implies that a tightening in macroprudential policies decrease individual bank risk (ceteris paribus). These results are in line with the existing literature on the effect of macroprudential policy tools on individual bank risk. Based on column 2 to 4, these effects can be explained by the capital-based and liquidity-based macroprudential polices. The main variable of interest, the interaction term between MP and MAP, is only significant (and only at the 10% level) and negative in column 2. This implies that a tightening in monetary policy reduces the initial effect of capital-based macroprudential polices on individual bank risk. Put differently, stricter capital-based macroprudential policy is less effective in periods of monetary tightening. The marginal effect of a one standard deviation tighter monetary policy environment, conditional on a one standard deviation tightening in capital-based macroprudential policy, is a 2.9% (=4.212 x 3.028 x 0.00226) decrease of the Z-score. The result of the interaction effect is in line with the existing literature, which finds that bank risk-taking induced by monetary policy is more pronounced when banks are better capitalized and are subject to more stringent capital requirements, and provides support for hypothesis 1.1. However, similar evidence is not found for borrower-based and liquidity-based macroprudential policy tools. One possible explanation for this is that capital-based tools make up the large majority of tools in the data sample. This reduces the statistical power of borrower-based and liquidity-based tools.

Column 5 to 8 present similar results, but with the systemic risk measure, the natural logarithm of SRISK, as dependent variable. Counterintuitively, all (significant) β_1 coefficients have a positive sign, indicating that a tightening in the macroprudential policy stance leads to an increase in the level of SRISK. This effect is explained by the capital-based and liquidity-based MAP sub-indices. This result is counterintuitive, as a tighter macroprudential policy environment is expected to be associated with a lower degree of systemic risk. One possible explanation for the result is that the SRISK data is only available for the largest banks in the sample, and that previous literature shows that the size of a bank is positively correlated with the effectiveness of macroprudential policy (e.g. Dell'Ariccia, 2016, Budnik & Bochmann, 2016).

The interaction coefficient between MP and MAP is significant (only at the 10% level) and positive in the case of the liquidity-based MAP index. This implies that a monetary tightening in a strict liquidity-based macroprudential policy environment has an amplifying effect on the level of SRISK of a bank. In particular, the marginal effect of a one standard deviation tightening (increase monetary policy surprise), conditional on a one standard deviation tightening in liquidity-based macroprudential policy, leads to a 15% (=4.28 x 1.842 x 0.0197) increase in the level of SRISK. This is again in line with the findings of previous literature and hypothesis 1.2 (Maddaloni and Peydró, 2013).

Table 3: Baseline panel OLS regression results.

	Dependent variable: Ln(Z-score)				*Dependent variable: Ln(SRISK)*			
	Total	Capital	Borrower	Liquidity	Total	Capital	Borrower	Liquidity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MAP	0.0493***	0.116***	-0.0138	0.142***	0.149***	0.194***	-0.241	0.279*
	(0.00813)	(0.0117)	(0.0496)	(0.0220)	(0.0449)	(0.0626)	(0.163)	(0.154)
MP*MAP	-0.000728	-0.00226*	-0.00233	-0.000173	-0.00164	0.00294	-0.0211	0.0183*
	(0.00102)	(0.00122)	(0.00509)	(0.00244)	(0.00486)	(0.00863)	(0.0165)	(0.0101)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.18	0.20	0.17	0.17	0.43	0.44	0.41	0.43
Observations	13,674	13,674	13,674	13,674	590	590	590	590
Number of banks	2,668	2,668	2,668	2,668	82	82	82	82

Note: This table presents the results of the panel OLS models. Column (1) to (4) report the results with the natural logarithm of Z-score as dependent variable. Column (5) to (8) report the results with the natural logarithm of SRISK as dependent variable. The MAP variable corresponds to the index reported above each column. The standard errors are in parentheses.***p<0.01,**p<0.05,*p<0.1.

4.2 Heterogeneous effects

To provide more insight in the baseline regression results, the focus will shift towards the influence of bank-specific factors on the provided findings. Tables 4 and 5 report the estimation results of equation (3), with $X_{b,c,t}$ representing either *Size* and *Leverage* as bank-specific factor of interest. Again, column (1) to (4) report the findings of the regressions with the natural logarithm of Z-score as dependent variable. Column (5) to (8) report the regressions with the natural logarithm of SRISK as dependent variable.

The results in column (1) to (4) of Table 4 suggest that the *Size* of a bank is a significant predictor in how monetary and macroprudential policy affect individual bank risk for borrower-based and liquidity-based macroprudential policy tools. For these tools, smaller banks are to a larger degree subject to the interaction effect between macroprudential and monetary policy. This can be observed for the coefficient β_4. For example, for a bank with is one standard deviation smaller (at the mean and compared to the mean) the interaction effect on individual bank risk of a tightening of one standard deviation of both monetary policy and borrower-based macroprudential policy is 1.5% (=0.00438 x 1.889 x 4.212 x 0.442) larger. For a bank with is one standard deviation smaller (at the mean and compared to the mean) the interaction effect on individual bank risk of a tightening of one standard deviation of both monetary policy and liquidity-based macroprudential policy is 2% (=0.00221 x 1.889 x 4.212 x 1.137). This is in accordance with hypothesis 2.1. Again, a possible explanation is that smaller banks are more sensitive to changes in both the macroprudential and monetary policy stance (e.g. Laeven et al., 2016; Cerutti, 2017). For the models with the natural logarithm of SRISK as dependent variable, displayed in column (5) to (8), the size of a bank is not a significant influence for the interaction effects on systemic risk.

Column (1) to (4) in Table 5 show that the degree of leverage shows to be a significant predictor for individual bank risk, as displayed by the regression with the capital-based macroprudential policy index. The main coefficient of interest (β_4) has a positive sign, indicating that banks with a lower degree of leverage are to a larger degree subject to the interaction effect between macroprudential and monetary policy. This implies that banks with a lower degree of leverage (as measured by total debt over total equity) face a larger degree of individual bank risk (as measured by a lower Z-score) after a monetary tightening and a macroprudential tightening. For example, for a bank which has a one standard deviation higher degree of leverage, the interaction effect on individual bank risk of a tightening of one standard deviation of both monetary policy and capital-based macroprudential policy is 6.6% (=0.000986*x 5.313 x 4.212 x 3.028) lower. This finding is not in line with the related literature and with hypothesis 2.2. However, for the regressions with the natural logarithm of SRISK as dependent variable, only a significant (at the 10% level) coefficient for the variable of interest is observed in Column (6), and has a positive sign. The interaction effect on systemic bank risk of a tightening of one standard deviation of both monetary policy and capital-based macroprudential policy is 10% (= 0.00178x 5.604 x 4.28 x 2.402) larger for a bank with a one standard deviation higher level of leverage. The sign of this result is in line with the related literature and hypothesis 2.2, which suggest that the interaction effect is more pronounced for more levered banks (Ely et al., 2021; Dell'Ariccia, 2016).

Finally, in Table 6 the results of the regression in equation (4) with bank *competition*, as measured by the Herfindahl-Hischman-index, are reported. In accordance with the related literature, the coefficient for HHI indicates that a higher degree of bank competition is associated with a lower Z-core, and thus a higher degree of bank risk (Andries et al., 2017). Furthermore, columns (1) to (4) indicate that bank concentration does not have an significant influence on the interaction effect of monetary and macroprudential policy on individual bank risk. However, column (5) and (8) of Table 6 report significant results for the impact of the degree of bank competition on the interaction effect, and is negative. In particular, an environment with a one standard deviation higher degree of bank competition and a one standard deviation tighter monetary policy and liquidity-based macroprudential policy is associated with a 1% (=0.0192 x 1.842 x 4.28 x 0.066) lower degree of SRISK of a bank. However, this result is substantially small which can be explained by, together with the remaining insignificance, by the findings of Ely et al. (2021). The influence of bank competition is highly dependent on the measure of bank risk, as well as the specific macroprudential policy tool. Since the variables for macroprudential policy are based on an index, the effect of individual tools are suppressed when these have opposite effects.

Table 4: Panel OLS regression results with bank size as heterogeneous effect.

	Dependent variable: Ln(Z-score)				*Dependent variable: Ln(SRISK)*			
	Total	Capital	Borrower	Liquidity	Total	Capital	Borrower	Liquidity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	`(8)
Ln(Size)	0.0692**	0.0785***	0.00354	0.0432*	1.721***	1.345***	1.406***	2.082***
	(0.0292)	(0.0268)	(0.0151)	(0.0223)	(0.275)	(0.282)	(0.241)	(0.309)
Ln(Size)*MP	0.00987**	0.00780**	0.00304*	0.00639**	-0.0359	-0.0450	-0.00772	-0.0109
	(0.00404)	(0.00344)	(0.00183)	(0.00283)	(0.0335)	(0.0393)	(0.0192)	(0.0239)
Ln(Size)*MAP	-0.00920***	-0.0163***	-0.0207	-0.0253**	-0.0587	0.0213	0.561*	-0.627***
	(0.00351)	(0.00484)	(0.0222)	(0.0107)	(0.0397)	(0.0479)	(0.327)	(0.204)
Ln(Size)*MP*MAP	-0.000986*	-0.00103	-0.00438*	-0.00221*	0.00629	0.00679	0.0177	0.0101
	(0.000512)	(0.000666)	(0.00261)	(0.00133)	(0.00572)	(0.00745)	(0.0168)	(0.0182)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time*Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.26	0.28	0.25	0.25	0.56	0.53	0.49	0.52
Observations	13,674	13,674	13,674	13,674	590	590	590	590
No. of banks	2,618	2,618	2,618	2,618	82	82	82	82

Note: This table presents the results of the panel OLS models. Column (1) to (4) report the results with the natural logarithm of Z-score as dependent variable. Column (5) to (8) report the results with the natural logarithm of SRISK as dependent variable. The MAP variable corresponds to the index as reported above each column. The standard errors are in parentheses.***p<0.01,**p<0.05,*p<0.1.

Table 5: Panel OLS regression results with leverage as heterogeneous effect.

	Dependent variable: Ln(Z-score)				*Dependent variable: Ln(SRISK)*			
	Total	Capital	Borrower	Liquidity	Total	Capital	Borrower	Liquidity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	`(8)
Leverage	0.0242*	0.0220*	0.0223***	0.0369***	-0.0529	-0.0673**	-0.0396	-0.161**
	(0.0145)	(0.0127)	(0.00785)	(0.0132)	(0.0371)	(0.0304)	(0.0319)	(0.0698)
Leverage*MP	0.00670***	0.00424**	0.00164*	0.00315**	0.00440	-0.00751	-0.00187	0.0111
	(0.00202)	(0.00179)	(0.000875)	(0.00156)	(0.00617)	(0.00484)	(0.00448)	(0.00991)
Leverage*MAP	0.000946	0.00224	-0.0141	-0.0114*	0.00659	0.00381	-0.159	0.0639*
	(0.00184)	(0.00196)	(0.0151)	(0.00670)	(0.00900)	(0.0100)	(0.146)	(0.0370)
Leverage*MP*MAP	-0.000971***	-0.000869**	-0.00168	-0.000950	-0.00159	0.00178*	-0.0187	-0.00678
	(0.000298)	(0.000355)	(0.00257)	(0.000797)	(0.00123)	(0.000982)	(0.0147)	(0.00489)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time*Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.25	0.28	0.25	0.25	0.52	0.53	0.49	0.52
Observations	13,674	13,674	13,674	13,674	590	590	590	590
No. of banks	2,618	2,618	2,618	2,618	82	82	82	82

Note: This table presents the results of the panel OLS models. Column (1) to (4) report the results with the natural logarithm of Z-score as dependent variable. Column (5) to (8) report the results with the natural logarithm of SRISK as dependent variable. The MAP variable corresponds to the index as reported above each column. The standard errors are in parentheses.∗∗∗p<0.01,∗∗p<0.05,∗p<0.1.

Table 6: Panel OLS regression results with bank concentration as heterogeneous effect.

	Dependent variable: Ln(Z-score)				*Dependent variable: Ln(SRISK)*			
	Total	Capital	Borrower	Liquidity	Total	Capital	Borrower	Liquidity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	`(8)
MAP	-0.00319	-0.0158	-0.191	-0.166**	0.00283	0.0105	-0.102	0.0403
	(0.0199)	(0.0230)	(0.186)	(0.0741)	(0.00600)	(0.00991)	(0.0744)	(0.0317)
MP*MAP	-0.00374**	-0.00451**	-0.0111	0.000650	0.00173**	0.00169	0.00328	0.00426**
	(0.00180)	(0.00202)	(0.0208)	(0.00393)	(0.000831)	(0.00112)	(0.00517)	(0.00195)
HHI	-4.151*	-3.676*	-3.731*	-5.862**	-0.289	-0.154	-0.361*	-0.200
	(2.306)	(2.066)	(1.946)	(2.306)	(0.302)	(0.208)	(0.209)	(0.280)
HHI*MP	-0.139	-0.129	0.142	0.0697	0.0490	0.0296	0.0120	0.0262
	(0.179)	(0.180)	(0.109)	(0.137)	(0.0345)	(0.0250)	(0.0125)	(0.0225)
HHI*MAP	0.169	0.380	1.224	1.435*	-0.00987	-0.0415	0.430	-0.161
	(0.138)	(0.267)	(1.186)	(0.763)	(0.0361)	(0.0739)	(0.377)	(0.155)
HHI*MP*MAP	0.0216	0.0344	0.0120	0.00414	-0.00851*	-0.00558	-0.0200	-0.0192**
	(0.0145)	(0.0268)	(0.115)	(0.0429)	(0.00472)	(0.00664)	(0.0311)	(0.00960)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.24	0.24	0.24	0.24	0.47	0.47	0.47	0.48
Observations	13,674	13,674	13,674	13,674	590	590	590	590
No. of banks	2,618	2,618	2,618	2,618	82	82	82	82

Note: This table presents the results of the panel OLS models. Column (1) to (4) report the results with the natural logarithm of Z-score as dependent variable. Column (5) to (8) report the results with the natural logarithm of SRISK as dependent variable. The MAP variable corresponds to the index as reported above each column. The standard errors are in parentheses.$***p<0.01$, $**p<0.05$, $*p<0.1$.

4.3 Robustness checks

4.3.1 Monetary policy asymmetry

The presented results ignore the possible asymmetric effect of monetary policy over the policy cycle (monetary easing vs. monetary tightening). To address this possible asymmetric effect of monetary policy, equation (2) is re-estimated by allowing the coefficient of monetary policy surprises to differ over easing and tightening periods. In particular, a dummy variable is created which takes the value of zero in periods of a negative monetary policy surprise (monetary easing), and a value of one in periods of a positive monetary policy surprise (monetary tightening). This dummy variable is interacted with the main variables of interest, and results in the following regression model;

$$Risk_{b,c,t} = \beta_0 + \beta_1 MAP_{c,t-1} + \beta_2\left(MP_t * MAP_{c,t-1}\right) + \beta_5(MAP_{c,t-1} * D_t) + \beta_6\left(MP_t * MAP_{c,t-1} * D_t\right) + \beta_7 BC_{b,t} + \beta_8 CC_{c,t} + \varphi_t + \varepsilon_{b,c,t} \quad (10)$$

in which D_t represents the dummy variable which captures the asymmetric monetary policy (surprise) effect. The remaining variables are similar as in equation (2). Note that the variables MP_t, D_t, and $(MP_t * D_t)$ are absent, since the inclusion of time fixed effects (φ_t) fully absorb the effect of monetary policy surprises.

The results of the estimation of equation (10) are presented in Table A7. Two key results come forward. Firstly column (2) suggests that the interaction effect of monetary and capital-based macroprudential policy is still negative, but that this effect is much larger in periods of monetary easing (D=1). Secondly, column (4) shows a positive and now significant for the interaction effect between monetary policy and liquidity-based macroprudential policy. However, this effect is apparent in periods of monetary tightening. This suggests that the findings are highly dependent on the monetary policy environment.

4.3.2 Geography asymmetry

As a second robustness check, an analysis is performed to investigate how the interaction effect differs across geographic region. Studies which are related to monetary policy, macroprudential policy and focus on the EA as sample, regularly make a similar distinction between the EA countries in the analysis of geographic differences (e.g. Damjanović and Masten, 2016; Samarina et al., 2019). For this study, this is relevant as a number of papers find that the transmission of monetary policy and macroprudential policy differs across the EA. For example, Belke et al. (2017) provide evidence that since the GFC the business cycles of EA core countries have synchronised towards each other, whereas the business cycles of EA periphery countries faced decreased synchronisation towards the EA core, which is related to a heterogeneous transmission of monetary policy across the EA. With respect to macroprudential policy, Meuleman and Vander Vennet (2020) find that macroprudential policy, as measured with a similar index as in this study, has heterogeneous effects on individual and systemic bank risk across different geographic regions across the Eurozone. The sign and size of these heterogeneous effects vary across the EA core, the EA periphery, Scandinavian countries and CEEC countries.

In this study, a distinction will be made between EA core countries, and the remainder of the EA countries, in which EA core countries are assigned similarly as in Meuleman and Vander Vennet (2020). The EA core countries are Austria, Belgium, France, Finland, Germany, Luxembourg and The Netherlands. Based on this classification, a dummy variable is created which takes the value of 1 for EA core countries, and the value of 0 for the remained of the EA countries. After interacting the dummy variable with the key variables of interest, this results in the following model;

$$Risk_{b,c,t} = \beta_0 + \beta_1 MAP_{c,t-1} + \beta_2 \left(MP_t * MAP_{c,t-1}\right) + \beta_3 (MP_t * CORE_i) + \beta_4 (MAP_{c,t-1} * CORE_i) + \beta_5 \left(MP_t * MAP_{c,t-1} * CORE_i\right) + \beta_6 BC_{b,t} + \beta_7 CC_{c,t} + \varphi_t + \varepsilon_{b,c,t} \quad (11)$$

in which $CORE_i$ represents the dummy variable which captures the difference between EA core countries and the rest of the EA periphery countries. The remaining variables are similar as in equation (2).

The results are presented in Table A8. Two interesting results can be observed. Firstly is the negative and highly significant sign of β_5 for the regression in Column 2. This means that the interaction effect between capital-based macroprudential policy and monetary policy is lower for EA core countries compared to the rest of the EA countries for individual bank risk. Moreover, the initial interaction effect even becomes positive, which suggests that the main findings (which show a positive effect between monetary policy and macroprudential policy) can be mostly assigned to EA core countries. This is still in line with the main results, as the majority of banks are from EA countries (74%). However, the opposite effect can be observed in Column 5, with systemic risk as dependent variable. Again, based on the regressions in equation 10, no clear effect that point in one direction can be derived.

4.3.3 Autocorrelation in Z-score

By construction, the Z-score dependent variable suffers from autocorrelation, since this measure relies on preceding values of the return on average assets of preceding periods, for the calculation of the standard deviation of the return on average assets. The value of Z-score in period *t* uses information which is also used for the calculation for the Z-score in period *t-1* and *t-2*. To assess if the results are driven by this autocorrelation, an alternative formulation for the Z-score is established to remove the constructed part of the autocorrelation. A similar method is employed in Goetz (2018), for a reconstruction of the Z-score to counter autocorrelation. Firstly, the data sample is split-up in non-overlapping periods of two consecutive years. Over these periods of two years, the standard deviation of the return on average assets is calculated which is needed for the construction of the Z-score. For all the remaining variables, the average value over the same two years is calculated and used in the analysis. For the calculation of the Z-score the average of the return on average assets and the average of the capital ratio is used. This ensures that in each period (previously a two-year period) is not correlated over time, as the information for the calculation of the standard deviation of the return on average assets is not used in other time periods. The results with this alternative Z-score measure as dependent variable are presented in Table A9 in the Appendix. The results are comparable to those of the baseline regression, which suggests that the findings are not caused by the autocorrelation in the original Z-score measure.

4.3.4 Alternative construction of MAP index/indices

Another concern is that the results are driven by the way the macroprudential policy indices are constructed. To examine whether this is the case, the macroprudential policy indices are reconstructed using an alternative specification. Specifically, the indices are recoded so that a specific policy receives a value of 1 if it is activated, and a value of 0 if it is deactivated. Hereby the index only captures how many policies are active simultaneously, and disregards scale and scope of each individual policy. The results using this alternative specification are reported in Table A10 in the Appendix. Again, the results are comparable with the baseline results, and suggests that the method of index construction is not decisive for the reported results.

Conclusion

This paper studies the interaction effect between macroprudential policy and monetary policy on bank risk in the Euro Area for the period 2006-2019. To ensure the exogeneity of the interaction effect, a measure for monetary policy is constructed which measures its surprise component, and includes aspects from the full spectrum of the yield curve. A comprehensive index and sub-indices for macroprudential policy are created which take in both the scale and scope of individual policy measures. The two created policy measures, and its interaction term are regressed on both individual and systemic bank risk measures in order to assess the effect of interest. Additionally, a deeper analysis is conducted to assess how the effect differs across different types of banks, and for banks that operate in different competitive environments, and geographic regions within the EA.

The main results of the analysis show that monetary policy and macroprudential policy have a positive interaction effect on individual bank risk, and this effect is the most pronounced when measured for capital-based macroprudential policy. This means that both a tightening of monetary and capital-based macroprudential policy increases individual bank risk relative to the initial effect on individual bank risk. Furthermore, this effect is stronger for larger banks, and banks that have a lower degree of leverage. Finally, further results show that the initial positive interaction effect is mainly applicable for banks from the EA core.

The results bring forward a number of policy recommendations. Firstly, the results expose that monetary and macroprudential policy counteract each other in ensuring stability. This result calls for more coordination of the two policies, and for more cooperation in the implementation of these policies between EA countries and on a supra EA level. Secondly, as the results point to large heterogeneous effects, the specifics of banks and countries should be a factor of consideration in the coordination and cooperation of the two policies.

This paper does come with a number of limitations. Firstly, this study focuses on the two aspects of bank risk, namely individual bank risk and systemic risk. However, this paper has only focussed on one measure of each type of risk. Further research should therefore extend towards more measures of bank risk. Secondly, this study solely focusses on banks. Therefore, it ignores the role of other financial institutions and the role of non-bank financing on the mix of monetary and macroprudential policy. Therefore, especially the role of non-bank financing can undermine the effect of macroprudential policy measured. Finally, the setup of the data sample is such that monetary policy is constant across all countries, while macroprudential policy varies across countries. Therefore, future studies should extend this field of research towards other regions across the earth to measure an optimal, or a least harming degree of monetary and macroprudential policy on bank risk.

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Appendix

Table A2: Weighing scheme of a macroprudential policy tool.

Type of policy action	Weight	Strengthening/Loosening	Sign	Final weight
Activation	1	Tightening	+	1
		Other/ambiguous impact		0
		Loosening	-	-1
Change in the level	0.25	Tightening	+	0.25
		Other/ambiguous impact		0
		Loosening	-	-0.25
Change in the scope	0.10	Tightening	+	0.10
		Other/ambiguous impact		0
		Loosening	-	-0.10
Maintaining existing level and scope	0.05	Tightening	+	0.05
		Other/ambiguous impact		0
		Loosening	-	-0.05
Deactivation	Accumulated index value drops to zero			

Note: Description of the weights to construct the macroprudential policy indices for each policy tool. Based on Meuleman and Vander vennet (2020).

Table A1: Broad categories of macroprudential policy instruments.

Capital-based	Minimum capital requirements
	Capital buffers
	Profit distribution restrictions
	Sectoral risk weights
	Loan loss provisioning rules
Borrower-based	Loan-to-value caps
	Debt-to-income and debt-service-to-income ratio's
	Other lending standards
Liquidity-based	Asset-based reserve requirements
	Liability-based reserve requirements
	Limits on longer-term maturity mismatch
	Limits on short-term maturity mismatch
	Limits on foreign exchange mismatch
Other instruments	Limits on large exposures
	Limits on exposures to sectors
	Taxes on financial institutions and activities
	Other policy actions

Note: Division of each policy across four broad categories according to Budnik and Kleibl (2018).

Table A3: MAP (sub)indices for EA countries.

Country	Total	Capital	Borrower	Liquidity	Other
Austria	4.568	1.55	0	1.5	1.518
Belgium	6.638	2.502	0	2.594	1.542
Cyprus	22.527	6.381	2.012	3.679	10.455
Estonia	3.024	1.892	0	1.838	-.705
Finland	4.507	2.462	.25	.891	.904
France	4.619	3.837	0	1.369	-.586
Germany	6.957	4.76	0	2.429	-.232
Greece	21.837	2.964	.465	5.482	12.926
Ireland	11.021	2.773	0	4.637	3.611
Italy	2.68	2.173	.043	0	.464
Lithuania	12.455	2.186	1.75	7.636	.883
Luxembourg	6.779	2.199	.464	.701	3.414
Latvia	13.751	4.449	3.458	2.182	3.662
Malta	5.41	1.046	0	3.436	.929
Netherlands	4.953	2.161	2.036	.072	.685
Portugal	5.704	3.298	-.982	2.649	.739
Slovak Republic	11.386	1.344	1.964	4.497	3.581
Slovenia	12.528	2.935	0	5.988	3.605
Spain	2.989	1.42	0	-.098	1.667
Total	*7.343*	*4.647*	*0.066*	*1.95*	*0.656*

Note: This table reports the mean of the (sub)index of the MAP stance for each EA country. The amounts are index-based.

Table A4: PCA analysis of monetary policy surprises.

Component	Eigenvalue	Difference	Proportion	Cumulative
1	10.1496	7.85981	0.7807	0.7807
2	2.28978	1.90752	0.1761	0.9569
3	0.382255	0.290752	0.0294	0.9863
4	0.082485	0.0426567	0.0063	0.9926
5	0.0398283	0.0186802	0.0031	0.9957
6	0.0211481	0.00892579	0.0016	0.9973
7	0.0122223	0.00396894	0.0009	0.9983
8	0.00825338	0.00195525	0.0006	0.9989
9	0.00629813	0.00259226	0.0005	0.9994
10	0.00370586	0.0016699	0.0003	0.9997
11	0.00203597	0.000575605	0.0002	0.9998
12	0.001466036	0.000520916	0.0001	0.9999
13	0.000939448	-	0.0001	1

Note: This table reports the results of the PCA analysis of the thirteen intra-day OIS changes around official monetary policy announcements ranging from one month to ten years. Column 3 reports the proportion of the variation explained by each component.

Table A5: Summary statistics of key variables for each EA country; full sample.

Country	No. of banks	Ln(Z-score)	Ln(Size)	Leverage	HHI
Austria	545	1.271	11.947	1.361	.042
Belgium	19	1.413	14.235	2.103	.135
Cyprus	20	1.306	13.076	.614	.142
Estonia	3	1.778	14.046	.476	.276
Finland	19	1.822	12.526	6.635	.308
France	180	1.671	15.104	4.862	.062
Germany	1121	2.554	13.697	.79	.026
Greece	6	0.141	15.986	.604	.175
Ireland	9	1.258	14.775	4.193	.066
Italy	449	1.208	13.528	2.352	.042
Latvia	7	1.372	13.648	1.022	.117
Lithuania	5	1.636	14.709	.146	.19
Luxemburg	44	1.336	14.308	3.017	.031
Malta	8	1.252	13.092	2.141	.139
Netherlands	17	1.384	15.580	8.367	.206
Portugal	48	0.693	12.641	2.244	.118
Slovak Republic	10	1.474	14.313	1.003	.125
Slovenia	11	0.830	14.532	.472	.114
Spain	97	1.831	13.867	1.236	.042
Total	*2618*	*1.87*	*13.424*	*1.536*	*.047*

Note: This table shows the number of banks and the averages of the key variables by country for the years 2006 to 2019 for the SRISK sample.

Table A6: Summary statistics of key variables for each EA country; SRISK sample.

Country	No. of banks	Ln(SRISK)	Ln(Size)	Leverage	HHI
Austria	6	4.291	16.850	2.031	.042
Belgium	2	8.781	15.909	.28	.135
Cyprus	2	5.644	16.120	.473	.142
Finland	3	5.519	16.944	6.899	.308
France	16	6.291	17.256	2.771	.062
Germany	8	8.130	17.779	9.291	.026
Greece	4	6.387	17.989	.737	.175
Ireland	3	5.339	15.019	.268	.066
Italy	19	5.408	17.229	3.243	.042
Lithuania	1	1.574	14.515	.185	.19
Malta	2	1.336	15.827	.293	.139
Netherlands	3	8.067	17.565	4	.206
Portugal	3	6.527	17.135	4.425	.118
Slovak Republic	1	1.06	16.421	1.462	.125
Spain	9	7.109	18.251	2.378	.073
Total	*82*	*6.028*	*17.929*	*3.619*	*.084*

Note: This table shows the number of banks and the averages of the key variables by country for the years 2006 to 2019 for the full sample.

Table A7: Panel OLS results with asymmetric effects over the monetary policy cycle.

	Dependent variable: Ln(Z-score)				*Dependent variable: Ln(SRISK)*			
	Total	Capital	Borrower	Liquidity	Total	Capital	Borrower	Liquidity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	`(8)
MAP	0.0270	0.0385	-0.116	0.115***	0.109	0.325	-0.618*	0.342*
	(0.0172)	(0.0295)	(0.301)	(0.0354)	(0.0682)	(0.234)	(0.363)	(0.195)
MP*MAP	-0.00856	-0.0277***	-0.0495	-0.00634	-0.00300	0.0542	-0.141	0.0407
	(0.00578)	(0.00987)	(0.121)	(0.00961)	(0.0149)	(0.0749)	(0.0905)	(0.0444)
D*MAP	0.0252	0.0954***	0.0134	0.0712**	-0.0701	-0.0983	0.512	-0.323
	(0.0171)	(0.0282)	(0.309)	(0.0342)	(0.0661)	(0.234)	(0.351)	(0.200)
D*MP*MAP	0.00727	0.0219**	0.0639	-0.00213	0.0205	-0.0495	0.108	0.0181
	(0.00618)	(0.0101)	(0.122)	(0.0106)	(0.0174)	(0.0731)	(0.118)	(0.0541)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.17	0.20	0.17	0.17	0.44	0.45	0.41	0.44
Observations	13,674	13,674	13,674	13,674	590	590	590	590
No. of banks	2,618	2,618	2,618	2,618	82	82	82	82

Note: This table presents the results of the panel OLS models with asymmetric effects over the monetary policy cycle. The variable D is a dummy variable which takes the value of 1 if MP>0, and 0 otherwise. Column (1) to (4) report the results with the natural logarithm of Z-score as dependent variable. Column (5) to (8) report the results with the natural logarithm of SRISK as dependent variable. The MAP variable corresponds to the index reported above each column. The standard errors are in parentheses.∗∗∗p<0.01,∗∗p<0.05,∗p<0.1.

Table A8: Panel OLS regression results with assymetric effect for EA core countries.

	Dependend variable: Ln(Z-score)				*Dependend variable: Ln(SRISK)*			
	Total	Capital	Borrower	Liquidity	Total	Capital	Borrower	Liquidity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	`(8)
MAP	-0.00211	0.000642	0.0156	-0.0608**	0.107**	0.269**	-0.462	0.0783
	(0.00965)	(0.0251)	(0.0593)	(0.0268)	(0.0419)	(0.132)	(0.465)	(0.154)
MP*MAP	-0.000423	0.00577*	-0.00237	8.83e-05	0.00398	0.0472*	-0.0271	0.0154
	(0.00144)	(0.00327)	(0.00718)	(0.00399)	(0.00377)	(0.0241)	(0.0276)	(0.0113)
EA core	-0.144	-0.0342	0.477***	-0.210**	0.449	0.311	0.332	-0.789
	(0.117)	(0.106)	(0.0711)	(0.0876)	(0.886)	(0.775)	(0.627)	(0.796)
EA core*MP	0.0108	0.0247*	0.0142*	0.0222*	0.0484	0.136	0.0166	0.0157
	(0.0169)	(0.0140)	(0.00782)	(0.0133)	(0.0971)	(0.0962)	(0.0471)	(0.0677)
EA core*MAP	0.0912***	0.101***	-0.0746	0.431***	-0.0334	-0.118	0.236	0.760**
	(0.0154)	(0.0256)	(0.0844)	(0.0502)	(0.0909)	(0.137)	(0.459)	(0.345)
EA core*MP*MAP	-0.00146	-0.00769**	-0.00787	-0.00647	-0.00697	-0.0493**	0.0465	0.00282
	(0.00195)	(0.00323)	(0.00991)	(0.00592)	(0.0129)	(0.0233)	(0.0327)	(0.0249)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.19	0.19	0.16	0.19	0.41	0.42	0.39	0.42
Observations	13,674	13,674	13,674	13,674	590	590	590	590
No. of banks	2,618	2,618	2,618	2,618	82	82	82	82

Note: This table presents the results of the panel OLS models. Column (1) to (4) report the results with the natural logarith of Z-score as dependent variable. Column (5) to (8) report the results with the natural logarithm of SRISK as dependent variable. The MAP variable corresponds to the index as reported above each column. EA core respresents a dummy variable which takes the value of 1 for banks from Austria, Belgium, France, Finland, Germany, Luxembourg and The Netherlands. The standard errors are in parentheses.***p<0.01,**p<0.05,*p<0.1.

Table A9: Panel OLS regression results with an alternative measure for Z-score.

	Dependent variable: Ln(Z-score)-1*			
	Total	Capital	Borrower	Liquidity
	(1)	(2)	(3)	(4)
MAP	0.0573***	0.163***	-0.0260	0.146***
	(0.00941)	(0.0138)	(0.0686)	(0.0246)
MP*MAP	-0.00353	-0.0126**	0.000887	-0.00562
	(0.00327)	(0.00506)	(0.0293)	(0.00808)
Bank controls	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
R-squared	0.15	0.16	0.14	0.15
Observations	7,534	7,534	7,534	7,534
Number of banks	2,618	2,618	2,618	2,618

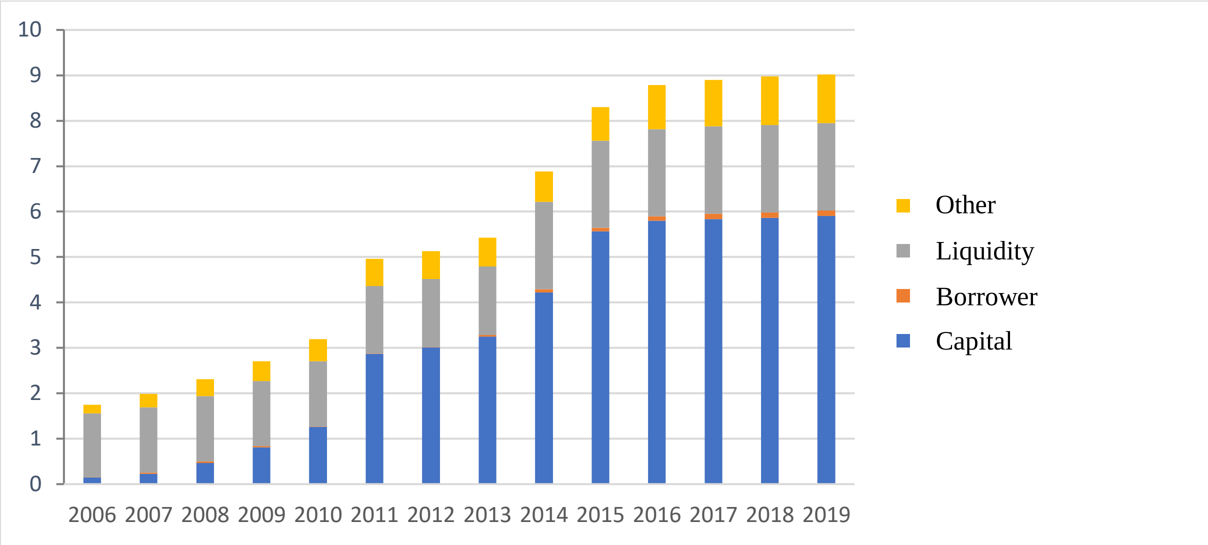
Note: This table presents the results of the panel OLS models with an alternative specification of Z-score as dependent variable, in natural logarithm. The MAP variable corresponds to the index reported above each column. The standard errors are in parentheses.***p<0.01,**p<0.05,*p<0.1.

Table A10: Panel OLS regression results with alternative MAP index/indices.

	Ln(Z-score)				*Ln(SRISK)*			
	Total	Capital	Borrower	Liquidity	Total	Capital	Borrower	Liquidity
	(1)	(2)	(3)	(4)	(6)	(7)	(8)	(9)
MAP	0.0616***	0.0806***	0.0221	0.161***	0.149***	0.194***	-0.241	0.279*
	(0.00919)	(0.0160)	(0.0522)	(0.0255)	(0.0449)	(0.0626)	(0.163)	(0.154)
MP*MAP	-0.00278**	-0.00389*	-0.00437	-0.00316	-0.00164	0.00294	-0.0211	0.0183
	(0.00110)	(0.00146)	(0.00893)	(0.00287)	(0.00486)	(0.00863)	(0.0165)	(0.0101)
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.17	0.17	0.17	0.17	0.44	0.44	0.41	0.42
Observations	13,674	13,674	13,674	13,674	590	590	590	590
Number of banks	2,618	2,618	2,618	2,618	82	82	82	82

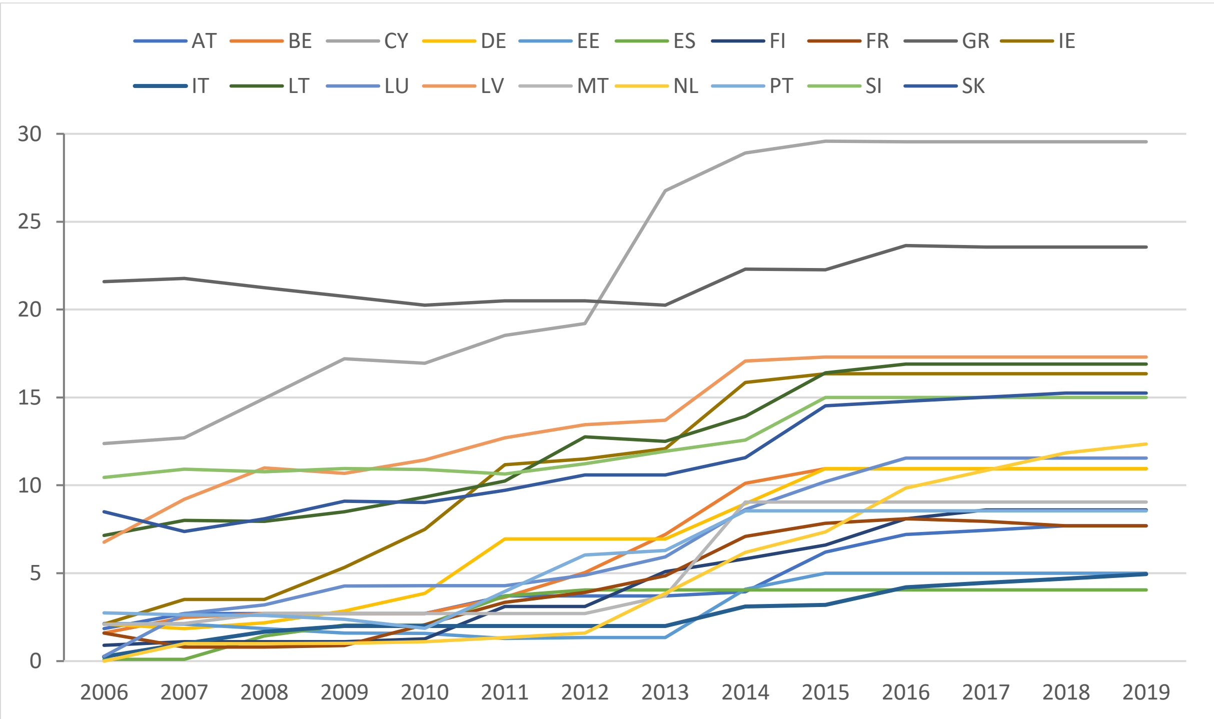
Note: This table presents the results of the panel OLS models with an alternative specification for the MAP indices. Column (1) to (4) report the results with the natural logarithm of Z-score as dependent variable. Column (5) to (8) report the results with the natural logarithm of SRISK as dependent variable. The MAP variable corresponds to the index reported above each column. The standard errors are in parentheses.***p<0.01,**p<0.05,*p<0.1.

Figure A1: Evolution of macroprudential policy in the Euro Area (EA).



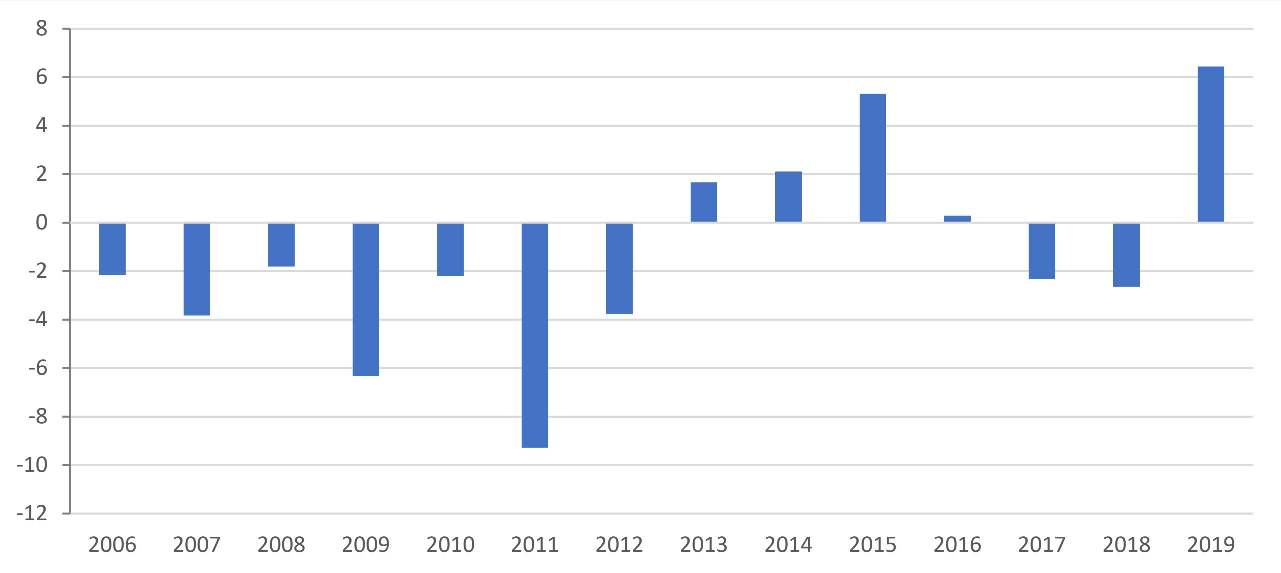
Note: This bar chart reports the EA wide evolution of macroprudential policies (MAP) as measured by the index specification of Meuleman and Vander vennet (2020) for the years 2006 until 2019. Each bar represents the total MAP index, including its four broad components for the corresponding year.

Figure A2: Evolution of the total MAP index for each EA country.



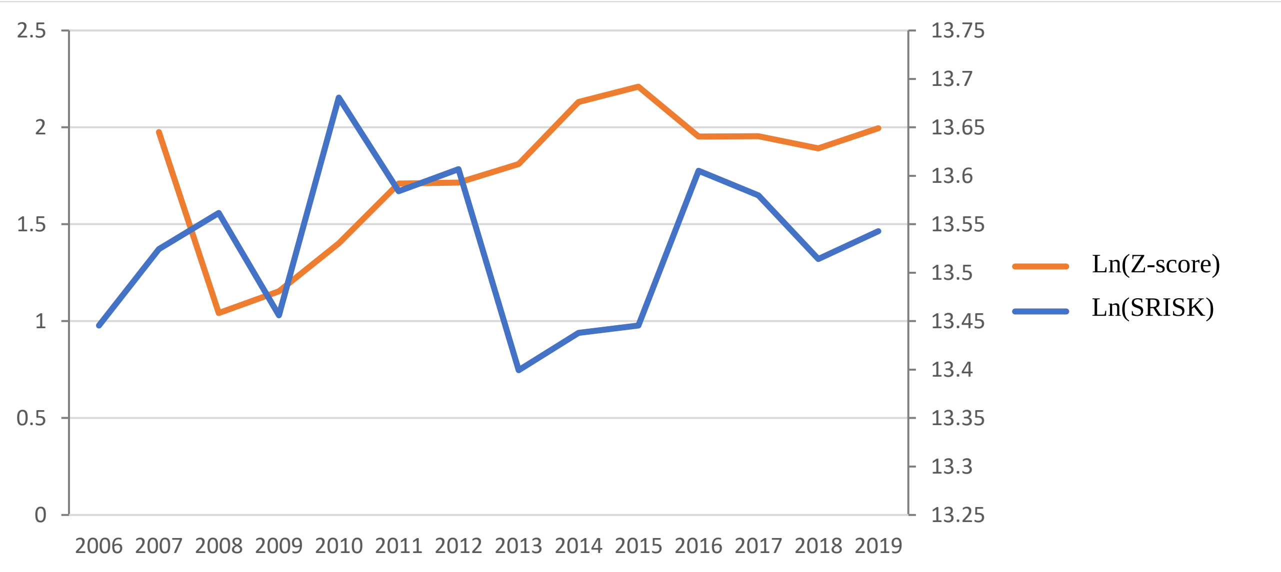
Note: This graph displays the evolution of the total MAP index for each individual EA country from 2006 until 2019. The legend reports each individual country with its ISO code.

Figure A3: Monetary policy surprises.



Note: This figure displays the yearly accumulated policy surprise element as constructed by a PCA analysis using high-frequency intra-day changes in OIS's around official monetary policy announcements ranging from one month to ten years.

Figure A4: Evolution of Z-score and SRISK.



Note: This graph presents the evolution of (the log-level) Z-score (in orange) and SRISK (in blue) from 2006 until 2019. The right axis reports the bank average values for Z-score across the EA for each year. The left axis reports the sum of SRISK for each year in the sample.