

THE SIXTEENTH YOUNG ECONOMISTS' SEMINAR

TO THE TWENTY-NINTH DUBROVNIK ECONOMIC CONFERENCE

Organized by the Croatian National Bank

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MacroPrudential Policy's influence on Monetary Policy's Interest Rate Channel. An empirical assessment for the European Union

Hotel "Hotel Palace" Dubrovnik May 24 – 25, 2023

Draft version Please do not quote



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Abstract

The deployment of Macroprudential Policy (MaPP), while offering the hope of safeguarding the economy from financial instability, could be influencing traditional channels of other policy spheres. In particular, there is reason to believe that MaPP and Monetary Policy (MonPol) interact. This paper offers empirical evidence for the European Union that MaPP does interfere in the traditional Interest Rate Channel (IRC) of MonPol. With a monthly panel of 28 EU countries (including the UK) from 2000 to 2019 I assess whether MaPP influences commercial banks' lending interest rates. A quantitative aggregate index of the MaPP stance for each EU country has been built using the ECB's MaPPed database. This aggregate MaPP index has also been disaggregated into demand-side and supply-side subindexes. Local projections have been used to address the research question. The empirical results indicate that supply-side MaPP tools affect commercial banks' lending interest rates. The same conclusions are reached when conducting the same analysis under a policy-shock methodology that addresses possible endogeneity concerns. It is hoped that these findings can aid policy-makers in the design, implementation and coordination of MonPol's policy rate changes and MaPP's tightenings/loosenings.

Key words: Macroprudential Policy; Monetary Policy; Interest Rate Channel.

1. Introduction

The Global Financial Crisis (GFC) consolidated the view that policies explicitly tackling financial instability and systemic risks are important for the management of our ever-increasing financialised economies. Given that the financial sector is not only a propagator of shocks stemming from other parts of the economy but can also be the originator of financial shocks, the increasingly widespread deployment of MacroPrudential Policy (MaPP) is very welcomed. It offers the hope of protecting economic activity from financial instability and crises.

The GFC also made it fairly apparent that Monetary Policy's (MonPol) inflation-targeting efforts are insufficient to guarantee financial stability. Furthermore, even if MonPol decides to counteract concentrated financial imbalances via policy rate changes, such interventions are likely to be too blunt (Bernanke, 2011). Therefore, it seems pretty sensible that MonPol should focus on price stability and that MaPP on financial stability. And indeed, it would be ideal if MonPol and MaPP were both effective in their tasks, since, then, GDP would look after itself. But of course, things are not so cross-cut. There will be instances where MonPol affects financial stability, and instances where MaPP affects price stability and GDP growth. That is to say, there are interactions between MaPP and MonPol. Consequently, their policy implementations must be coordinated to unleash complementarities and avoid instances where MaPP neutralises MonPol tigthenings/loosenings and vice versa.

We are entering a new policy era in which MaPP will be gaining more prominence. Given that the deployment of MaPP can potentially influence the effectiveness of MonPol, it is crucial that their interactions are studied. This research topic will allow policy makers to design and coordinate MaPP and MonPol such that their implementations and interactions yield the desired policy objectives.

Increasingly, there is a lot of talk and discussion on the interaction between MonPol and MaPP (Martin, et al., 2021; Vollmer, 2021; Brussière, 2020). There is, however, not so much empirical evidence of concrete instances where MaPP influences MonPol. In this paper I shall empirically evaluate whether MaPP influences MonPol's Interest Rate Channel (IRC). Given that we are now leaving the Zero Lower Bound (ZLB), the interest rate pass-through from the Central Bank's policy rate to commercial banks' interest rates will rebecome important for the management of the economy. It is important to assess whether the now widespread deployment of MaPP is influencing MonPol's traditional IRC.

This paper's main research question is the following: can MaPP affect the interest rates commercial banks charge their customers, having controlled for MonPol? I deem this research question to be policy-relevant. Agents make decisions based on (amongst other things) the interest rate banks charge on loans. Given than the CB's policy rate is a key driver of bank interest rates, MonPol can influence the consumption, production, saving and investment decisions of the economy and thus affect economic growth, inflation and house prices. However, if we find that MaPP also affects banks' lending interest rates, MaPP and MonPol must be coordinated to avoid undesirable policy outcomes. For example, lack of coordination can lead to a MaPP loosening neutralising a MonPol tightening. Another example could be a simultaneous and uncoordinated MaPP and MonPol tightening that increases bank lending interest rates more than expected and have a bigger downward effect on GDP than anticipated.

I have built a monthly panel of 28 European Union (EU) countries (including the recently Brexited UK) from January 2000 to June 2019. Panel Local Projections (Jorda, 2005) have been employed. My results indicate that MaPP does affect the IRC of MonPol. Supply-side tools (those affecting the decisions of banks) are found to have a stronger bearing than demand-side tools (those affecting the decisions of borrowers) on banks' loan interest rates. And in particular, supply-side capital-based MaPP tools have the largest influence on interest rates. This is a valuable insight for policy as it implies that MonPol and MaPP should be coordinated.

To alleviate endogeneity concerns from the baseline Local Projection analysis, a policy-shock analysis has also been conducted, very much in the style of Chari et al. (2022) and Ahnert et al. (2021). The policy-shock methodology requires estimating a first-stage regression of the MaPP variable on an array of lagged macrofinancial variables that could affect its changes. The residuals from this first-stage regression can be considered to be a more exogenous measure of changes in the MaPP variable. These residuals are then introduced in the baseline Local Projection instead of their respective original MaPP variable. The results from the policy-shock analysis support the baseline Local Projection findings.

Section 2 of the paper sets the scene by describing the traditional Interest Rate Channel (IRC) of Monetary Policy (MonPol). Section 2 will also offer a quick review of MacroPrudential Policy (MaPP), as well as a discussion on how MaPP could be affecting the IRC. Section 3 offers a literature review of relevant empirical studies for the research question at hand. Sections 4 and 5, respectively, discuss the data and methodology used for the baseline Local Projection analysis. Section 6 hosts the results of the baseline Local Projections. Section 7 briefly outlines the policy-shock methodology; describes the additional data required for the first-stage regression; and displays the results using the residuals from the first stage regression instead of the MaPP indexes in the baseline Local Projections. Section 8 offers concluding remarks.

2. The Interest Rate Chanell (IRC) and MacroPrudential Policy (MaPP)

The IRC of MonPol works as follows: changes in the Central Bank (CB) policy rate (i_{CB}) lead to changes in the interbank interest rate (i_o) . The interbank rate will hover more obediently close to the new i_{CB} the narrower the CB-determined corridor is in the interbank market for reserves. And given that the interest rate commercial banks charge their borrowers (i_b) is a mark-up over the interbank rate, i_b will also change after changes in the CB policy rate (Mojon, 2000). Ultimately, given that Households (HHs) and NonFinancial Corporations (NFCs) make their consumption, investment, saving and production decisions as a function of the prevailing interest rates (amongst other factors), changes in the CB policy rate can have impacts on economic activity (de Bondt, 2005), and consequently on CPI inflation, GDP growth, unemployment and on the House Price and Stock Price Indexes (respectively, HPI and SPI).

$$i_{CB} \rightarrow i_o \rightarrow i_b \rightarrow \begin{cases} CPI \\ GDP \\ HPI \\ SPI \end{cases}$$



Figure 1. Central Bank policy rate, Interbank interest rate and the aggregate bank lending rate to HHs and NFCs in 18 EU countries (percent per annum, in real terms).

The graphs of Figure 1 reflect how the inflation-deducted interbank interest rate (ri_interBnk) is very close to the real CB policy rate (ri_CB), and how the aggregate real interest rate banks charge their borrowers

(ri_HHNFC) is a mark-up over the interbank rate. The reader can find the same graphs for the remaining EU countries in figure A.1 of the Appendix.

MaPP has the overarching objective of minimising and managing financial instability so that long-term GDP growth can go on uninterrupted by financial crises. It has two intermediate goals (IMF, 2013, 2014a, 2014b; IMF-FSB-BIS, 2016): i) the prevention of systemic vulnerabilities; ii) the resilience of the banking sector. The first intermediate objective is achieved by taming the credit cycle so that HHs and NFCs don't become excessively indebted and fragile to financial conditions, and also to avoid the positive feedback between asset prices and credit. Resilience is conceptualised in terms of the banking system's capacity, mainly through adequate capitalisation, to, conditional on a financial crisis not having been avoided, cushion the wave of nonperforming loans and to avoid a credit-crunch (BCBS, 2010a).

There are supply-side and demand-side tools for MaPP to achieve its objectives. Supply-side tools influence the lending decisions of banks. Demand-side tools influence the borrowing decisions of HHs and firms. Examples of supply-side tools are capital-based tools (such as the Countercyclical Capital Buffer or the Capital Adequacy Ratio); liquidity-based tools (such as the Liquidity Coverage Ratio or the Net Stable Funding Ratio); and loan-based tools (such as limits on credit growth or Loan Loss Provisions). Examples of demand-side tools are Loan-to-Value or Debt-Service-to-Income ratios. A consensus seems to be emerging that indicates that capital-based tools are good for building resilience by lessening the severity of recessions and by quickening recovery (Jorda, et al., 2021), while demand-side tools are more effective at curbing the credit cycle (Cerutti et al., 2017).

Since the recent widespread deployment of MaPP, commercial banks incur extra costs in order to comply to such new financial regulations (Elliot, 2009). For instance, capital requirements increase the funding costs of extending new loans as capital is more expensive than banks' principal sources of funding, namely deposits and debt. Another example would come from liquidity requirements, which reduce banks' net interest income since banks reduce their holdings of higher-return assets in exchange for high-quality liquid assets, in addition to shifting away from cheaper short-term borrowing to more expensive long-term borrowing. Commercial banks, amongst other reactionary measures to new MaPP regulation, will pass on these additional costs and foregone net-interest income to their borrowers by increasing their lending rates (Elliot et al., 2012; BCBS, 2010b; Slovik et al., 2011).

The invasion of MaPP in MonPol's IRC can be depicted in the following schematic way:

$$i_{CB} \rightarrow i_o \rightarrow i_b$$

$$\bigwedge$$

$$\bigwedge$$

$$MaPP$$

3. Literature Review

The empirical literature on the effectiveness of MaPP, although increasingly large, is mainly concerned with its effects on credit and house prices (Araujo, et al. 2020). In this section we shall exclusively review the relatively scant empirical literature that has evaluated the effect of MaPP tools on commercial banks' interest rates.

In table A.2 of the Appendix, the reader can find a summary of papers that have studied whether MaPP tools can affect banks' loan pricing decision. As can be seen from that table, the literature, as it currently stands, is inconclusive as to whether MaPP does or does not affect interest rates. From the 11 papers listed in table A.2, five of them report statistically insignificant effects on banks' interest rates (Banerjee and Mio, 2018; Behn et al., 2016; Bonner, 2016; Dasatti et al., 2019; Ferrari et al., 2017), while the remaining papers do find a

statistically significant effect (Ahnert et al., 2021; Akram, 2014; Auer et al., 2022; Basten, 2020; De Schryder et al. 2021; Martins et al., 2013). Most papers are at the bank-level for a given country evaluating with difference-in-difference techniques the impact of a particular tool activated on a specific date on the interest rates of new loan contracts.

As mentioned earlier, most papers studying MaPP and bank interest rates are conducted at the bank-level. They estimate the treatment effect of a given MaPP tool on the interest rate of a given loan contract with respect to an untreated bank. I am, however, interested in the macro effect of MaPP on the banking system's aggregate interest rates, not on relative effects between banks. From the papers list in table A.2, only three are at the macro level. Ahnert et al. (2021) with an annual panel of 26 countries showed that Foreign Exchange (FX) MaPP regulation increases the interest rate banks charge on FX loans. Akram et al (2014) studied for Norway how the Capital Adequacy Ratio (CAR) increases banks' lending rates and consequently affects GDP with a quarterly Vector Error Correction Model (VECM). De Schyder et al. (2021), although more interested in analysing the effect of MaPP on credit and house prices, found, for a quarterly panel of 13 EU countries, that Lending Standard Restriction (LSR) MaPP tools increase the mortgage rate banks charge their borrowers.

Given that there is inconclusive evidence on the effect of MaPP on bank interest rates, I hope this paper is able to contribute towards stablishing a consensus on whether these effects exist and if so which type of MaPP tools exert the strongest pressure on banks' lending interest rates. Furthermore, given that there is very little empirical research at the economy-wide level of MaPP's effect on bank interest rates, I hope that my analysis on a monthly panel of 28 EU countries (UK included) can be considered valuable new empirical evidence at the macro level.

4. Data for baseline Local Projection analysis

To answer the research question "after controlling for MonPol, does Macroprudential Policy (MaPP) affect the interest rates of commercial banks loans?" I have built a monthly frequency panel of 28 EU countries (including the UK) from January 2000 to June 2019. The list of countries can be found in the Appendix table A.1., which also reports the year in which countries became EU members and members of the Euro Area (EA). This section of the paper shall now proceed to describe the data employed in my analysis. The data involves MaPP indices, commercial bank interest rates and other macro-financial control variables.

4.1. Macroprudential Policy Data

The source of the MaPP data is from the ECB's MacroPrudential Policy Evaluation Database (MaPPed) (Budnik and Kleibl, 2018). The MaPPed database is composed of eleven tool categories: Capital Buffers (CB); Lending Standard Restrictions (LSR); Leverage (LVR); Limits of Credit Growth Volume (LCGV); Limits on Large Exposures and Concentrations (LLEC); Liquidity Restrictions and Limits on Currency and Maturity Mismatches (LRLCMM); Loan Loss Provisions (LLP); Minimum Capital Requirements (MCR); Other Measures (OM); Risk Weights (RW); and Taxes (TAX). Furthermore, within each of these eleven tool categories there are various types of tools. For instance, the MCR category is composed of four tools: Capital Adequacy Ratios (CAR), Tier 1 capital Ratio (T1), Common Equity Tier 1 capital Ratio (CET1), and Core T1 capital Ratio (CORET1). Additionally, several tools have a sectorial dimension. That is, certain tools target a specific sector and not all the borrowing sectors. For example, Risk Weights can be applied exclusively on bank loans to Households (HH) for Residential Real Estate (RRE) or for consumption (cons), or on bank loans to Nonfinancial Corporations (NFC) for Commercial Real Estate (CRE) or for other purposes (oNFC). The Appendix tables A.3.1 to A.3.11 report the 11 MaPPed tool categories, the tools within each category and the sectorial dimension of the tools. The MaPPed database is information rich. It contains information on the decision, announcement and effective dates of the policy actions for each tool; it also distinguishes between policy actions that are legally binding and recommendations, as well as on whether the policy action can be considered countercyclical in nature or not. But one of the main interesting aspects of the MaPPed database is that it chronicles the life cycle of each tool: from the activation of the tool, to changes in the level and in its scope, to its deactivation. This offers greater information than databases that simply report the dates a given tool was activated and deactivated, like the iMaPP database introduced by Alam et al. (2019).

Meuleman and Vennet (2020) are the first to convert the information in the MaPPed database into a quantitative index of the MaPP stance for the 28 countries composing the database. The table below and the paragraph bellow it summarise how the index is built.

Type of tool	Weight	Loosening /tightening	Impact	Final Weight
Type of tool	weight	Loosening/ lightening	impact	
action				(weight*impact)
Activation	1	Tightening	1	1
		Other/ambiguous	0	0
		Loosening	-1	-1
Change in the	0.25	Tightening	1	0.25
level		Other/ambiguous	0	0
		Loosening	-1	-0.25
Change in the	0.1	Tightening	1	0.1
scope		Other/ambiguous	0	0
		Loosening	-1	-0.1
Maintaining the	0.05	Tightening	1	0.05
level and scope		Other/ambiguous	0	0
		Loosening	-1	-0.05
Deactivation	The cumulative sum of the tool is reset to 0			

Table 1. Weighting scheme to construct the life cycle of a policy action over time. (An adapted version of Table 1 from Meuleman and Vennet (2020)).

Each MaPP tool can undergo 4 types of policy actions before it is deactivated: activation, change in the level, change in the scope, and maintenance of the existing level and scope. Each of these 4 types of actions receives a weight. Activations receive a weight of "1", changes in level receive a weight of "0.25", changes in the scope receive "0.1", and maintaining the level and scope of a tool receives the value of "0.05". The idea behind these weights is that the activation of a tool has a stronger impact than an increase in its existing level, and that increasing the level of a tool has a stronger effect than a change in its scope. Depending on whether these 4 types of actions are considered Tightenings, Loosening or ambiguous, their weights are, respectively, multiplied by "1", "-1" or "0". Therefore, for example, a tool that is activated with a tightening character receives the final weight of "1", and a loosening change in the level of a tool would receive the final weight of "-0.25", which would subtract 0.25 from the cumulative MaPP index up to that date.

For each tool an index is constructed. The value of the index for each tool in month t is the cumulative sum of the sequence of its policy actions measured with the abovementioned weighting system up to month t. When a tool is deactivated, the cumulative sum of past actions is reset to "0". Meuleman and Vennet (2020) build an aggregate MaPP index by summing up all the indices of all the tools. For further details on the method of building a MaPP index from the MaPPed database refer to Meuleman and Vennet (2020) and to Fernandez-Gallardo and Paya (2020) who build an Euro Area-wide MaPP index.

Figure 2 below illustrates how the index is built. Figure 2 plots the sequence of policy actions involving liability-based Reserve Requirements (LCGV_LRR) in Croatia. The index value begins at 0 and jumps to the

value of 1 in July 2004, when the authorities activate the LCGV_LRR. The index stays at the value of 1 until February 2005 when there is a tightening change in the level, bringing the index to the value of 1.25. In May 2005 the index attains the value of 1.5 after another tightening change in the level. In December 2005 it climbs to the value of 1.75 after another tightening change in the level. In June 2006 it reaches the value of 2 after its last tightening change in the level. The index for this policy action life cycle remains at 2 until September 2010, because in October 2010 the tool is deactivated, bringing its index value to 0.



Figure 2. Example of the life cycle of a policy action in Croatia involving liability-based Reserve Requirements.

I have followed the method of Meuleman and Vennet (2020) to build quantitative MaPP indices for each of the 28 countries. Given that announcement dates can be considered more exogenous than implementation dates of MaPP tool actions (De Schyder et al. 2021,) I have used the announcement dates of policy actions, but have had to use the implementation dates when the announcement dates were not available. I have excluded countercyclical policy actions from the indexes due to endogeneity concerns with such type of actions (Fernández-Gallardo, 2023). The indexes considered both legally binding and recommendatory policy actions. I have also decomposed the total MaPP index into a demand-side MaPP subindex and a supply-side MaPP subindex.

$$MaPP_{TOT} = CB_{TOT} + LSR_{TOT} + LVR_{TOT} + LCGV_{TOT} + LLEC_{TOT} + LRLCMM_{TOT} + LLP_{TOT} + MCR_{TOT} + OM_{TOT} + RW_{TOT} + TAX_{TOT}$$
(1)

Equation (1) states the aggregate MaPP index ($MaPP_{TOT}$) is equal to the sum of the indices of the 11 categories of the MaPPed database. Each category is itself equal to the sum of the indices of the tools that compose it. For instance, MCR_{TOT} is equal to the sum of the CAR index, T1 index, CET1 index and the CORET1 index.

Figure 3 below shows the $MaPP_{TOT}$ index for 9 EA countries and 9 non-EA countries. Figure A.2 from the Appendix hosts the same graph for the remaining EU countries.

$$MaPP_{TOT} = MaPP_{dem} + MaPP_{sup} \tag{1.1}$$

$$MaPP_{dem} = LSR_{LTV_{tot}} + LSR_{DSTI_{tot}} + LSR_{MAR_{tot}} + LSR_{OIR_{tot}} + LSR_{LTI_{tot}}$$
(2)

 $MaPP_{sup} = CB_{TOT} + LSR_{OR_{tot}} + LSR_{LOI_{tot}} + LSR_{LVPL_{tot}} + LVR_{TOT} + LCGV_{TOT} + LLEC_{TOT} + LRLCMM_{TOT} + LLP_{TOT} + MCR_{TOT} + OM_{TOT} + RW_{TOT} + TAX_{TOT}$ (3)





The demand-side MaPP index $(MaPP_{dem})$ is composed of tools that influence the decisions of the loan borrowers. $MaPP_{dem}$ (Equation 2) is formed of the following Lending Standard Restrictions (LSR) tools: Loanto-Value ratio (LTV), Debt Service to Income ratio (DSTI), Maturity Amortisation Restrictions (MAR), Other Income Restrictions (OIR), and the Loan-to-Income ratio (LTI). The supply-side MaPP index ($MaPP_{sup}$) is formed by tools that influence the lending decisions of banks (Equation 3): all the tools within the Capital Buffer category (CB_TOT); three tools from the Lending Standard Restrictions category, which are Other Restrictions (LSR_OR_tot), Limits on Interest rates (LSR_LOI_tot) and Limits on Volume of Personal Loans (LSR_LVPL_tot); Leverage (LVR_TOT); and all the tools within Limits to Credit Growth Volume (LCGV_TOT), within Limits on Large Exposures and Concentrations (LLEC_TOT), within Liquidity Restrictions and Limits on Currency and Maturity Mismatch (LRLCMM_TOT), within Loan Loss Provisions (LLP_TOT), within Other Measure (OM_TOT), within Risk Weights (RW_TOT); and taxes (TAX_TOT).

Figure 4 plots the $MaPP_{dem}$ and the $MaPP_{sup}$ index for 18 EU countries. Figure A.3. of the Appendix displays the same graph for the remaining EU countries.

Figure 4. The Demand- and Supply-side MaPP index ($MaPP_{dem}$ and $MaPP_{sup}$) for 9 EA countries and 9 non-EA countries.



Given that the supply-side MaPP index has much more variability than the demand-side counterpart, I have disaggregated $MaPP_{sup}$ into four types of supply-side actions (Equation 3.1), very much in line with the disaggregation of Alam et al. (2019).

$$MaPP_{sup} = MaPP_{supLoan} + MaPP_{supCap} + MaPP_{supGen} + MaPP_{supOth}$$
(3.1)

$$MaPP_{supLoan} = LSR_{ORtot} + LSR_{LOItot} + LSR_{LVPLtot} + LCGV_{ARRtot} + LLP_{TOT} + LLEC_{TOT}$$
(4)

$$MaPP_{supCap} = CB_{TOT} + LVR_{TOT} + MCR_{TOT} + RW_{TOT}$$
(5)

$$MaPP_{supGen} = LCGV_{LRR_{tot}} + LRLCMM_{TOT} + TAX_{TOT}$$
(6)

$$MaPP_{sup0th} = OM_{TOT} \tag{7}$$

The Supply-side loan-based MaPP tool index (Equation 4) is composed of Other Restrictions (LSR_OR_TOT), Limits on interest rates (LSR_LOI_TOT), Limits on Volumes for Personal Loans (LSR_LVPL_TOT), Asset-based Reserve Requirements (LCGV_ARR_TOT), Loan Loss Provisions (LLP_TOT) and Limits on large Exposures and Concentration limits (LLEC_TOT). Equation (5) describes the capital-based supply-side MaPP index. It is composed of Capital Buffers, the leverage ratio, minimum capital requirements and risk Weights. The General-based supply-side MaPP index is built according to Equation (6). It is the sum of liability-based Reserve Requirements, all liquidity requirements and taxes. Equation (7) reflects the other supply-side MaPP tool index, which is composed of mainly Crisis Management tools and debt resolution policies.





Figure 5 above displays the $MaPP_{supLoan}$, $MaPP_{supCap}$ and the $MaPP_{supGen}$ indices for 9 EMU countries and 9 non-EMU countries. The $MaPP_{supOth}$ index is not displayed as it has very little variability. The reader can find the same graph for the remaining EU countries in Figure A.4 of the Appendix. As can be observed, it seems that $MaPP_{supLoan}$ is generally deployed more than $MaPP_{supCap}$ for most countries.

4.2. Commercial Bank lending interest rate Data

The source of loan interest rate data has been the ECB's Statistical Data Warehouse. For some countries, when possible, the interest rate data has been backdated with data from their respective Central Banks' websites. The interest rates pertain to new business (i.e., not the interest rate on outstanding loans). Interest rates are on loans denominated in the local currency of each country. The interest rates are expressed in percent per annum.

In terms of lending interest rates to NFCs we have the following interest rates: i_NFC_A2A and i_NFC_A2Z. The i_NFC_A2A is the interest rate banks charge NFCs for loans other than revolving loans and overdrafts, convenience and extended credit card debt. The i_NFC_A2Z is the interest rate banks charge NFCs for revolving loans and overdrafts and credit card debt. The i_NFC_A2Z data has no disaggregation into different maturities. The i_NFC_A2A data is separated into the interest charged on such loans with a maturity less than 1 year, with a maturity between 1 and 5 years, with a maturity between 5 and 10 years, and with maturity over 10 years. I have built a weighted average of the interest rate that banks charge NFC using the volumes of new business of each of the loan-maturities. This weighted average interest rate charged on NFCs I shall call i_NFC. The most common type of loan NFCs receive in both EA and nonEA countries are revolving loans and

overdrafts and credit card debt (i_NFC_A2Z). In the analysis we shall analyse the weighted average interest rate i_NFC and also i_NFC_A2Z.

With regards to lending interest rates to HHs we have the following interest rates: a) i_HH_A2B which is the interest rate banks charge HHs for loans for consumption excluding revolving loans and overdrafts, convenience and extended credit card debt. We shall call this interest rate i_cons; b) i_HH_A2C which is the interest rate charged for loans for house purchase excluding revolving loans and overdrafts, convenience and extended credit card debt. We shall call this interest rate i_cons; b) i_HH_A2C which is the interest rate charged for loans for house purchase excluding revolving loans and overdrafts, convenience and extended credit card debt. We shall call this interest rate i_mort.

For EA countries the interest rates i_cons and i_mort were already available to download as the weighted average of their interest rates with different maturities. For nonEA countries, however, I had to compute the weighted average i_cons and i_mort with their respective volumes of new loans with different maturities.

In the EA, the most common mortgage rate at which HHs get indebted is with a maturity of over 10 years (i_mort_o10), while in nonEA countries it is with a maturity between 1 and 5 years (i_mort_1to5). In the EA the most common interest rate for consumption loans is that with a maturity over 5 years (i_cons_o5), while for nonEA countries it is for loans with a maturity under 1 year (i_cons_u1). We shall also analyse i_mort_o10 and i_cons_o5 in the EMU sample, as well as the i_cons_u1 and i_mort_1to5 in the nonEA sample.

Figure 7 displays the real interest rate of the weighted average i_NFC and of i_mort for a selection of EA and nonEA countries. In figure A.6 of the Appendix the reader can find the same graphs for the remaining EU countries. The real interest rates (ri_NFC and ri_mort) were obtained by deducting the annual inflation rate from the nominal interest rates.



Figure 7. Real interest rates on lending to NFCs and to HHs for mortgages for 18 EU countries.

In the analysis we shall also evaluate the influence of MaPP tools on the aggregate interest rate, which we call i_HHNFC. This i_HHNFC is the weighted average of the interest rate charged on HHs for consumption, on HHs for mortgages and on NFCs. The weights I used to build this aggregate i_HHNFC are obtained from the outstanding amount of loans. For instance, the weight for i_cons in i_HHNFC is $L_{cons}/(L_{cons} + L_{mort} + L_{NFC})$. The reason for using outstanding amount of loans, as opposed to volumes of new loans, is because for EA countries the volumes of the various maturities of i_NFC_A2A are at the EMU level, not country by country.

4.3. Central Bank Policy rates, Interbank interest rates and shadow rates

The source for Central Bank Policy rates for all countries, except for Bulgaria, is from the Bank of International Settlements (BIS). For Bulgaria I have used the money market rate obtained from the International Monetary Fund (IMF). For several countries, when possible, I have backdated the policy rates with money market rates from the IMF.

For EA countries, the interbank rate is the EONIA (Euro OverNight Index Average), obtained from the ECB's Statistical Data Warehouse. For non-EA countries the interbank rate is the money market rate obtained from the IMF. Given that since the GFC many central banks' policy rates were set at zero or close to zero and with very little variability for a prolonged period, we shall use shadow when possible. Since 2009 shadow rates reflect MonPol better than the CB policy rate, this is so because shadow rates overcome the ZLB problem by accounting for unconventional MonPol interventions such as Quantitative Easing (QE) (Wu and Xia, 2016). For the UK, EA countries and Sweden, I have used their respective shadow rates from January 2009 onwards, as opposed to continuing with their interbank interest rates, precisely to capture MonPol unrelated to its policy rate. For the UK and for EA countries I have used the Wu and Xia (2016) shadow rates of the Bank of England and the ECB, obtained from the website https://sites.google.com/view/jingcynthiawu/shadow-rates. For Sweden I have used the Sveriges Riskbank shadow rate put forth by De Rezende and Ristiniemi (2023), available from https://www.rafaelbderezende.com/shadow-rates..

4.4. Other Macro-Financial Data

Here follows a brief description of the other macro-financial variables I use as controls in my empirical investigation.

The data source for the CPI data is the ECB's Data Statistical Warehouse. I have used the Harmonised Index of Consumer Prices (HCIP) with 2015 as the index year. I have seasonally adjusted the HCIP series with the ARIMA X-11 procedure.

The VSTOXX is the implied market volatility across a basket of Eurozone stocks and is based on the real-time market prices of Euro STOXX 50 options. It is obtained from two websites: <u>www.stoxx.com</u> and from <u>www.wsj.com</u>. The VSTOXX is in daily frequency. I turned it into monthly frequency by computing the daily average in each month.

The forecasted year-on-year (YoY) growth of EA's GDP was obtained from the OECD (the Organisation for Economic Co-operation and Development). This variable is in quarterly frequency. I turned it into monthly frequency by using the quarterly value in each of the three months that compose it.

Bank concentration, measured as the asset-share of the three largest commercial banks in the banking sector. It is obtained from the Global Financial Development Database (GFDD) from the World Bank. This variable is in annual frequency. I use the same procedure as Meuleman and Vennet (2020) to turn annual variables into monthly frequency. All the months of a given year take the value of the previous year. For example, the 2009 annual value of the Bank Concentration variable is used for all the months of 2010.

Bank Crisis dates are obtained from Laeven and Valencia (2020). It is a dummy variable taking the value of "1" in the month a banking crisis began.

The Killian Index is a measure of global real economic activity. It is obtained from the Federal Reserve Bank of Dallas.

Lastly, for the monthly analysis I have built three indicators which can be loosely interpreted as expected demand for bank loans: Expected aggregate demand for credit, which I label E(aggDem); Expected firm demand [E(firmDem)]; and expected credit demand from HHs, which I christened E(hhDem). Including the growth rate of bank loans as a regressor with bank interest rates as the dependent variable would clearly be suffering from reverse causality. Therefore, I shall use these loose measures of expected credit demand as regressors instead. These three indicators of expected demand were built from the Eurostat's Economic Sentiment Indicators (ESI). I shall now proceed to explain how I constructed them.

The ESI is built as follows: ESI = 0.40ICI + 0.30SCI + 0.20CCI + 0.05RCI + 0.05BCI. Where ICI stands for the Industrial Confidence Indicator; SCI for the Services Confidence Indicator; CCI for the

Consumer Confidence Indicator; RCI for the Retail Confidence Indicator; and BCI for the Construction Confidence Indicator. The ESI is a weighted average of the values of its five indicators. Each of these 5 indicators is constructed from the answers to survey questions. Instead of using ESI, I decided to just use the information each indicator offers with respect to the survey questions concerning expected demand. The next paragraph outlines how I did so.

From the questions that compose the ICI I used the answer from its question number five: "Production expectations for the months ahead", which I call E(indProd). From the questions that compose SCI I used the answer from its question number 3: "Expectation of the demand over the next 3 months", which I call E(servDem). From the questions that compose CCI I used the answers from its question number 2 and number 4, respectively: "Financial situation over next 12 months" and "General economic situation over next 12 months, which I call, respectively, E(HHfin) and E(HHeco). From the questions that compose RCI I used the answer to its question number 4: "Business activity expectations over the next 3 months", which I call E(retBiz). From the questions pertaining to BCI, I have used the answers from its question number 3 and 4, respectively: "Evolution of your current overall order books" and "Employment expectations over the next three months". I call these, respectively *buildEvol* and E(buildEmp). I build the expected demand for credit from the building sector as the average of its two questions I use: E(build) = 0.50buildEvol + 0.50E(buildEmp).

I can build my three indicators of expected bank credit demand as follows:

$$E(hhDem) = 0.50E(HHfin) + 0.5E(HHeco)$$
(14)

$$E(firmDem) = 0.50E(indProd) + 0.35E(servDem) + 0.075E(retBiz) + 0.075E(build)$$
(15)

$$E(aggDem) = 0.40E(indProd) + 0.30E(servDem) + 0.20E(hhDem) + 0.05E(retBiz) + 0.05E(build)$$
(16)

Figure 8, below, plots the YoY growth rate of total loans to the private sector(loanTOT_YoY) and E(aggDem) for a selection of 9 countries. As can be seen the two time-series are pretty-well correlated. In Figures A.7 and A.8 of the Appendix, the reader can find the graphs that plot the YoY growth rate of loans to NFC and E(firmDem), and the YoY growth rate of loans to HHs and E(hhDem). As can be seen by these figures, these three proxies for credit track the YoY growth rates of loans remarkably well.

Figure 8. The similarity between our proxy for aggregate credit demand [E(aggDem)] and the YoY growth rate of total loans to the private sector.



5. Methodology for the Baseline Local Projection analysis

In this section I shall proceed to describe the empirical strategy I have chosen in order to investigate my research question, which I remind the reader is the following: can MaPP affect commercial banks' lending interest rates? I shall be relying on Local Projections (LP) (Jorda, 2005). All regressions use Driscoll-Kraay standard errors which are robust to general forms of cross-sectional and temporal dependence (Driscoll and Kraay, 1998).

Here are the LP specifications for the assessment of Macroprudential Policy's influence on banks' lending interest rates. I use a monthly panel from January 2000 to June 2019 with 28 countries. For $RI_{s,i,t}$ where $s = \{HHNFC, mort, NFC\}$ and for h = 1, ..., 24 I estimate:

$$\Delta_{h}RI_{s,i,t} = \alpha_{i}^{h} + \beta_{s,TOT}^{h} \Delta MaPP_{TOT,i,t} + \sum_{k=1}^{6} \theta_{s,k}^{h} \Delta RI_{s,i,t-k} + \sum_{k=1}^{6} \delta_{s,k}^{h} \Delta IbI_{i,t-k} + \sum_{k=1}^{6} \gamma_{s,k}^{h} CC_{t-k} + \sum_{k=1}^{6} \pi_{s,k}^{h} \Delta^{YoY} BnkConcent_{i,t-k} + \sum_{k=1}^{6} \varphi_{s,k}^{h} ED_{i,t-k} + \sigma_{s}^{h} BnkCris_{i,t} + u_{s,i,t+h}$$
(20)

$$\Delta_{h}RI_{s,i,t} = \alpha_{i}^{h} + \beta_{s,dem}^{h} \Delta MaPP_{dem,i,t} + \beta_{s,sup}^{h} \Delta MaPP_{sup,i,t} + \sum_{k=1}^{6} \theta_{s,k}^{h} \Delta RI_{s,i,t-k} + \sum_{k=1}^{6} \delta_{s,k}^{h} \Delta IbI_{i,t-k} + \sum_{k=1}^{6} \gamma_{s,k}^{h} CC_{t-k} + \sum_{k=1}^{6} \pi_{s,k}^{h} \Delta^{YoY} BnkConcent_{i,t-k} + \sum_{k=1}^{6} \varphi_{s,k}^{h} ED_{i,t-k} + \sigma_{s}^{h} BnkCris_{i,t} + u_{s,i,t+h}$$

$$(21)$$

Where $\Delta_h RI_{s,i,t} = RI_{s,i,t+h} - RI_{s,i,t}$. $RI_{s,i,t}$ stands for real interest of loan type *s* in country *i* in month *t*. $\Delta MaPP_j$ denotes the month-on-month (MoM) change in the *j* MaPP index. I evaluate the effect of $\Delta MaPP_j$ for $j = \{TOT, dem, sup\}$. In equation (20) we are interested in the coefficient $\beta_{s,TOT}^h$, which captures the percentage point change in the bank real interest rate type s ($s = \{HHNFC, mort, NFC\}$) *h* months after a one-point index change in the $MaPP_{TOT}$ index. In equation (21) we simultaneously estimate the effect from the demand- and supply-side MaPP subindexes, respectively coefficients $\beta_{s,dem}^h$ and $\beta_{s,sup}^h$.

 $IbI_{i,t}$ stands for interbank interest rate in country *i* in month *t*. Note, however, that from January 2009 onwards I used, instead of the interbank rate, the shadow rates of the ECB for Euro Area countries, the shadow rate of the Bank of England for the UK and the shadow rate of the Sveriges Riskbank for Sweden. I include up to 6 lags of the month-on-month (MoM) change of the real interest under regression ($\Delta RI_{s,i,t}$), up to 6 lags of the MoM change in the real interbank interest rate ($\Delta IbI_{i,t}$), up to 6 lags of the YoY change in bank concentration ($\Delta^{YoY}BnkConcent_{i,t}$). I also include up to 6 lags of EA's forecasted YoY growth as well as of the VSTOXX index. These last two regressors, common to all EU countries, are inside the regressor CC_t . A bank crisis dummy is also included into the specification ($BnkCris_{i,t}$). Country fixed effects are also employed (α_i^h). $u_{s,i,t+h}$ denotes the error term of the LP at horizon *h*.

Depending on the real interest rate under regression, the regressor $ED_{i,t}$ in (20 and 21) changes, which is our loose measure of expected loan demand, of which we include up to 6 lags. When the real interest rate

considered is $RI_{mort,i,t}$ we use $E(hhDem_{i,t})$; when the real interest rate under regression is $RI_{NFC,i,t}$ we use $E(firmDem_{i,t})$; and when the real interest under investigation is the $RI_{HHNFC,i,t}$ we use $E(aggDem_{i,t})$.

I also evaluate which of the three types of supply-side MaPP indices has a stronger bearing on interest rates. To do so I rely on the following LP specification. For $RI_{s,i,t}$ where $s = \{HHNFC, mort, NFC\}$ and for h = 1, ..., 24 I estimate:

$$\Delta_{h}RI_{s,i,t} = \alpha_{i}^{h} + \beta_{s,dem}^{h} \Delta MaPP_{dem,i,t} + \beta_{s,L}^{h} \Delta MaPP_{supLoan,i,t} + \beta_{s,C}^{h} \Delta MaPP_{supCap,i,t} + \beta_{s,G}^{h} \Delta MaPP_{supGen,i,t} + \sum_{k=1}^{6} \theta_{s,k}^{h} \Delta RI_{s,i,t-k} + \sum_{k=1}^{6} \delta_{s,k}^{h} IbI_{i,t-k} + \sum_{k=1}^{6} \gamma_{s,k}^{h} CC_{t-k} + \sum_{k=1}^{6} \pi_{s,k}^{h} \Delta^{YoY} BnkConcent_{i,t-k} + \sum_{k=1}^{6} \varphi_{s,k}^{h} ED_{i,t-k} + \sigma_{s}^{h} BnkCris_{i,t} + u_{s,i,t+h}$$

$$(22)$$

All the regressors in equation (22) are the same as those in (21), the only change has been that I now simultaneously estimate three-type of supply-side MaPP indexes in the specification, as opposed to just the aggregate supply-side MaPP subindex. We keep the demand-side MaPP regressor ($\Delta MaPP_{dem,i,t}$) as a control.

Before turning to results, it is timely to note that these LPs, in addition to estimating them with the full sample of 28 countries, I shall also estimate them exclusively on a panel of EA countries, and also on a panel of nonEA countries.

6. Results of Baseline Local Projections

In terms of interpreting the LP graphs that follow, note that the shaded areas represent the confidence bands at 1.645 standard deviations. The Local Projections coloured in black pertain to results estimated on the full sample of countries. The blue Local Projections are the results for the panel of EA countries, and orangy-red LPs are those of the nonEA panel.



Figure 9. Local Projection results on the aggregate interest rate on loans (ri_HHNFC). Full sample of countries.

In figure 9, for the full sample of countries, I plot the LPs of the different MaPP indexes considered on the real aggregate interest rate of bank loans (ri_HHNFC). It can be observed that $\Delta MaPP_{TOT,i,t}$ does have a positive and statistically significant effect on ri_HHNFC (up to around 12 months). These LPs also reveal that supply-side MaPP tools have a stronger and more statistically significant effect on ri_HHNFC than demand-side tools. The disaggregation of the supply-side MaPP index into loan-based, capital-based and general supply-side MaPP tools was also revealing. Capital-based tools are the supply-side type MaPP tools that have the strongest and most statistically significant effect on ri_HHNFC. The estimated effect for all these LPs on ri_HHNFC are always below 0.5 percentage points for any horizon.



Figure 10. Local Projection results on the interest rate of mortgage loans (ri_mort). Full sample of countries.

The conclusions from the LPs on ri_HHNFC are also reach with the LPs on ri_mort and ri_NFC, respectively Figure 10 and 11. For both interest rates on mortgage loans and loans to NFCs, $\Delta MaPP_{TOT,i,t}$ is found to have a positive and statistically significant effect. This effect is mainly driven by $\Delta MaPP_{sup,i,t}$, since $\Delta MaPP_{dem,i,t}$ is rarely statistically significant. Furthermore, in turn, capital-based MaPP tools are driving the effect of the supply-side MaPP tools on both ri_mort and ri_NFC.

Figure 12 plots the LP of $\Delta MaPP_{TOT,i,t}$, $\Delta MaPP_{dem,i,t}$ and $\Delta MaPP_{sup,i,t}$ on ri_HHNFC estimated with a panel of EA countries (top row, blue line) and with a panel of nonEA countries (bottom row, orangy-red line). For both the EA and nonEA panel, $\Delta MaPP_{sup,i,t}$ has the most statistically significant effect on ri_HHNFC. In Figure 13 I look into which of the three supply-side MaPP indexes has the most statistically significant effect on ri_HHNFC for a panel of EA countries (top row, blue line) and for a panel of nonEA countries (bottom row, orangy-red line). As can be seen, for both EA and nonEA countries, capital-based tools are the supply-side tools with the strongest and most statistically significant effect. In nonEA sample, loan-based supply-side MaPP tools are also found to be statistically significant during the first few horizons.

Figures 14 and 15 plot the plot the LP of the different MaPP indexes on ri_mort with a panel of EA countries (top row, blue line) and with a panel of nonEA countries (bottom row, orangy-red line). The conclusions for ri_mort are very similar to those for ri_HHNFC: supply-side MaPP tools are more statistically significant than demand-side tools, and capital-based tools are driving the results for supply-side tools. Nevertheless, for nonEA countries loan-based supply-side tools are also found to have a statistically significant effect on ri_mort at several horizons.



Figure 11. Local Projection results for the interest rate on loans to NFCs (ri_NFC). Full sample of countries.

Figure 12. Local Projection results of the total MaPP index and the demand-side and supply side-subindexes on the aggregate interest rate on loans (ri_HHNFC). EA countries (top row) and nonEA countries (bottom row).



Figure 13. Local Projection results of the supply-side Loan-based, capital-based and general MaPP indexes on the aggregate interest rate on loans (ri_HHNFC). EA countries (top row) and nonEA countries (bottom row).



Figure 14. Local Projection results of the total MaPP index and the demand-side and supply side-subindexes on the interest rate of mortgage loans (ri_mort). EA countries (top row) and nonEA countries (bottom row).



Figure 16 and 17 plot the plot the LP of the different MaPP indexes on ri_NFC with a panel of EA countries (top row, blue line) and with a panel of nonEA countries (bottom row, orangy-red line). The analysis on ri_NFC yielded similar conclusions to ri_HHNFC and ri_mort. Although supply-side MaPP tools have a more statistically significant effect than demand-side tools in the EA sample, demand-side MaPP tools are also found to be statistically significant at several horizons in the nonEA sample. And again we see, that for ri_NFC too, capital-based tools are driving the results for supply-side tools.

Figure 15. Local Projection results of the supply-side Loan-based, capital-based and general MaPP indexes on the interest rate of mortgage loans (ri_mort). EA countries (top row) and nonEA countries (bottom row).



Figure 16. Local Projection results of the total MaPP index and the demand-side and supply side-subindexes on the interest rate of loans to NFCs (ri_NFC). EA countries (top row) and nonEA countries (bottom row).



Figure 17. Local Projection results of the supply-side Loan-based, capital-based and general MaPP indexes on the interest rate of loans to NFCs (ri_NFC). EA countries (top row) and nonEA countries (bottom row).



In Figures A.9 to A.13 of the Appendix, the reader will find the LPs conducted on specific interest rates, as opposed to weighted averages of interest rates on loans with different maturities. Concretely, I shall estimate the LP on ri_NFC_a2z on the full sample of countries, as well as on a panel of just EA countries and on another panel of nonEA countries. For the panel of EA countries, ri_mort_010 has been studied, and ri_mort_1to5 for the panel of nonEA countries. The results on these more specific interest rates confirm the baseline results.

7. Data and Methodology of Policy-Shock analysis

As with any econometric analysis, endogeneity is always a concern. Before I delve into the methodology of the policy-shock analysis, I wish to first argue why I feel reasonably confident that reverse-causality is not a major concern in my baseline Local Projection regressions.

As argued by Meuleman and Vennet (2020), the concern that MaPP tightenings/loosenings are reacting to changes in the macrofinancial environment, as opposed to being fully exogenous, is mitigated with monthly frequency data. It is hard to imagine MaPP reacting within the same month to a shock in systemic risk. The facts that policy decisions and implementations take time, monthly frequency data mutes these reverse-causality anxieties. Note also, precisely to further control for reverse causality, that I have explicitly omitted any MaPP actions which the MaPPed database catalogues as countercyclical. Furthermore, to the extent that MaPP authorities monitor loan volumes more than loan interest rates in their tightening/loosening decisions, it can be argued that reverse-causality is less of an issue with interest rates than with loan volumes as the dependent variable. Additionally, due to the monthly frequency, the time series are long which alleviates the Nickel Bias stemming from the inclusion of lags of the dependent variable as a regressor.

The policy-shock approach has previously been used in the empirical literature to build exogenous monetary policy shocks (Furceri, et al., 2016), fiscal policy shocks (Auerbach et al., 2013), and more recently also in the MaPP arena (Ahnert et al., 2021; Chari et al., 2022). The attractiveness of this methodology lays in its ability to extract a measure of MaPP changes orthogonal to macrofinancial observables. This is achieved by estimating a first-stage regression where the dependent variable will be $\Delta MaPP_i$ for $j = \{TOT, dem, sup\}$,

which were our regressors of interest in the baseline Local Projection. The residuals from the first-stage regression of each $\Delta MaPP_{TOT}$, $\Delta MaPP_{dem}$ and $\Delta MaPP_{sup}$ are stored and respectively, called $\hat{u}_{MaPPtot}$, $\hat{u}_{MaPPdem}$ and $\hat{u}_{MaPPsup}$. Thereafter, we use these residuals instead of their respective $\Delta MaPP_{j}$ in the baseline Local Projection, equations (20) and (21).

In the first-stage regression it is necessary to use a rich set of regressors to increase the specification's explanatory power with regards to the MoM changes in the aggregate, demand-side and supply-side indexes. In addition to variables described and used up to here in the paper, the policy-shock analysis requires more macrofinancial variables. Data for the Real Effective Exchange Rate (REER) was retrieved from the Bruegel Broad Datasets; as a measure of financial openness, I have used the Chinn-Ito Index (Chinn and Ito, 2008); the industrial production index (IPI) was obtained from the ECB's SDW. Although the ECB's SDW offers bank loan data, its sectorial disaggregation is only available from 2003, therefore I have obtained longer bank credit data à la Bezemer et al. (2017). This required retrieving bank credit data, as well its sectorial disaggregation, from the data portal of each of the countries' Central Bank. I have also obtained two annual variables from the World Bank, the Z-score and the ratio of nonperforming loans to outstanding loans (NPL2L). The Z-score measures the probability of default of a country's commercial banking system. The quarterly Real House Price Index (RHPI) data from the Bank of International Settlements (BIS) has been turned into monthly frequency via linear interpolation.

The first-stage regression also includes some regressors related to crises, retrieved from the Laeven and Valencia (2020) database. The variable $AnyCris12_{i,t}$ takes the value "1" for country *i* in month *t* if it suffered either a banking, currency or sovereign-debt crises during the last 12 months. For each month *t*, the variables $numBnkCris_t$, $numCurrCris_t$ and $numSovCris_t$, respectively, count the number of bank, currency and sovereign-debt crises across all the countries in the Laeven and Valencia (2020) database. These last three crisis variables have no country *i*-subindex since it takes the same value for each country.

For each $j = \{TOT, dem, sup\}$ we estimate the following first-stage regression on $\Delta MaPP_i$:

$$\Delta MaPP_{j,i,t} = \alpha_i + \sum_{k=1}^{6} \beta_{j,k} MACROFIN vars_{i,t-k} + \delta_j ChinnIto_{i,t-1} + \theta_{j,1} AnyCris12_{i,t-1} + \theta_{j,2} AnyCris12_{i,t-12} + u_{MaPPj,i,t}$$
(23)
$$\hat{u}_{MaPPj_{i,t}} = \Delta MaPP_{j,i,t} - \Delta \widehat{MaPP}_{j,i,t}$$
(24)

Equation (23) is estimated with Driscoll-Kraay standard errors. α_i hosts the country fixed-effects. The variables contained in the regressor $MACROFINvars_{i,t}$ are meant to capture aspects of the macrofinancial environment that may prompt a MaPP tightening or loosening. The selection of variables is mainly inspired by the first-stage regression specification of Chari et al. (2022). We have the following: the VSTOXX index; the YoY growth rate of inflation, of the $IPI_{i,t}$ and of the $RHPI_{i,t}$; the MoM change in the $REER_{i,t}$; the inflation-deflated MoM change in the interbank interest rate; the YoY growth rate of real loans to HHs; the YoY growth rate of real loans to NFCs; the proxy for expected aggregate Credit demand ($E_aggDem_{i,t}$) (see section 4.4); the $Zscore_{i,t}$ of each country's banking system; the YoY change in the ratio of $NPL2L_{i,t}$; $numBnkCris_t$, $numCurrCris_t$ and $numSovCris_t$.

After estimating equation (23) for each $\Delta MaPP_{TOT,i,t}$, $\Delta MaPP_{dem,i,t}$ and $\Delta MaPP_{sup,i,t}$, we retrieve their respective residuals, $\hat{u}_{MaPPtot_{i,t}}$, $\hat{u}_{MaPPdem_{i,t}}$ and $\hat{u}_{MaPPsup_{i,t}}$, as expressed in equation (24). They represent movements in the MaPP indexes that could not be accounted for by the observable macrofinancial variables. These three residuals can be considered as exogenous MaPP shocks, and, as such, we are interested in substituting in $\hat{u}_{MaPPtot_{i,t}}$ for $\Delta MaPP_{TOT_{i,t}}$ in equation (20). $\Delta MaPP_{dem,i,t}$ and $\Delta MaPP_{sup,i,t}$, from equation (21) are, respectively, substituted by $\hat{u}_{MaPPdem_{i,t}}$ and $\hat{u}_{MaPPsup_{i,t}}$. For each regression estimated at each of

the 24 horizons, a bootstrap with 500 repetitions is used due to the fact the residuals I now use as regressors have been generated during the first-stage regression.

Due to the large number of regressors and lags in equation (23), the results of the first-stage regressions occupy a lot of space, and for that reason they have been omitted from the paper. The first-stage regressions are available upon request to the author.



Figure.18. Policy-shock methodology Local Projections.

Figure 18 hosts the results obtained from the policy-shock analysis. The results of the baseline LP are confirmed with this alternative methodology. For all three interest rates (ri_HHNFC, ri_NFC and ri_mort), the total MaPP index is statistically significant for all horizons; demand-side tools are never found to be statistically significant; supply-side tools have a statistically significant effect. I have not conducted the policy-shock analysis on the three types of supply-side MaPP indexes because they have less variability than the aggregate supply-side MaPP index. Consequently, their first-stage regression would not be very satisfactory due to this lack of variability.

8. Conclusion

Given that MaPP is increasingly being deployed across the world, its interactions with MonPol are also increasingly becoming important. The Interest Rate Channel (IRC) is a key policy channel of MonPol, and as such, it is worth evaluating whether MaPP is interfering in it. To do so, this paper has evaluated whether MaPP influences commercial banks' loan interest rates. My empirical findings indicate that MaPP does have a statistically significant effect on loan interest rates. This finding can be catalogued as prima-facie evidence that MaPP is interfering with MonPol's traditional Interest Rate Channel.

My analysis has also revealed that supply-side tools have a stronger bearing on loan interest rates than demand-side tools. Furthermore, my result shows that capital-based MaPP tools have the strongest influence on interest rates out of all the supply-side MaPP tools. This can be explained by the accounting explanation of Elliot (2009): Given that capital-based MaPP tools make banks fund more of their lending with capital and less with cheaper debt and deposit funding, banks charge higher interest rates on their loans.

The baseline results are confirmed in the alternative policy-shock methodology. The findings are policyrelevant, as they highlight that MonPol and MaPP do affect each other (they interact). Consequently, MonPol and MaPP actions should be coordinated.

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APPENDIX

Figure A.1. Central Bank policy rate, Interbank interest rate and aggregate bank lending rate to HHs and NFCs in the remaining EU countries (percent per annum, in real terms).



Table A.1. EU and EA countries

EU member		EA member
since	Country	since
1995	Austria	1999
1958	Belgium	1999
2007	Bulgaria	No
2013	Croatia	No
2004	Cyprus	2004
2004	Czechia	No
1973	Denmark	No
2004	Estonia	2011
1995	Finland	1999
1958	France	1999
1958	Germany	1999
1981	Greece	2001
2004	Hungary	No
1973	Ireland	1999
1958	Italy	1999
2004	Latvia	2014
2004	Lithuania	2015
1958	Luxembourg	1999
2004	Malta	2008
1958	Netherlands	1999
2004	Poland	No
1986	Portugal	1999
2007	Romania	No
2004	Slovakia	2009
2004	Slovenia	2007
1986	Spain	1999
1995	Sweden	no
	UK	
1973	(31Jan20)	no

Paper	Country and time	Frequency	Macro or micro	MaPP tool	Interest rate	Method	Result
Ahnert et al. (2021)	panel of 26 countries	annual	country	FX regulations tools	on FX loans	panel FE regressions	statistically significant interest rate increase
Akram (2014)	Norway. 1992 to 2010	quarterly	country	Capital Adequacy Ratio	average interest rate of total bank loans	VECM	statistically significant interest rate increase
Auer et al (2022)	Switzerland. 2012 to 2013	monthly	bank	Countercyclical Capital Buffer	average interest rate charged by bank <i>b</i> to firm <i>f</i>	Difference- in- Difference	statistically significant interest rate increase
Banerjee and Mio (2018)	UK. 2010 and 2012	quarterly	bank	Individual Liquidity Guidance	average interest rate on loans to non-financial sector	propensity score matching	no statistically significant impact on interest rate
Basten (2020)	Switzerland. 2012 to 2014	monthly	bank	Countercyclical Capital Buffer	weighted average mortgage interest rate spread	Difference- in- Difference	statistically significant increase in interest rate
Behn et al. (2016)	Germany. 2008 to 2011	quarterly	bank	procyclical capital regulation	interest rate on specific loan	treatment effect	no statistically significant effect
Bonner (2016)	Netherlands. 2004 to 2011.	monthly	bank	similar to the Liquidity Coverage Ratio	Weighted average interbank interest rate spread of bank <i>b</i> ; lending rate spread bank <i>b</i> charges on firms	regression discontinuity design	Statistically significant effect on interbank interest rates; No statistically significant effect on corporate lending rates.
Dassatti et al. (2019)	Uruguay. 2008	monthly	bank	Reserve Requirement	average interest rate bank <i>b</i> charges firms in industry <i>j</i>	Difference- in- Difference	no statistically significant effect on interest rates
De Schryder et al (2021)	13 EU countries. 1999 to 2018.	quarterly	country	MaPP index	mortgage interest rate	Local Projections	statistically significant effect at several horizons
Ferrari et al. (2017)	Belgium. 2012 to 2015.	monthly	bank	Sectoral Risk Weight	weighted-average mortgage interest rate of bank <i>b</i>	Difference- in- Difference	no statistically significant effect
Martins et al. (2013)	Brazil. 2010 to 2012.	monthly	bank	within sector Capital requirements	interest rate spread charged on borrower <i>i</i> by bank <i>b</i>	treatment effect	statistically significant effect on interest rates

Table A.2. Summary table of empirical papers studying the effect of MaPP on commercial bank interest rates.

A.3. The 11 MaPP tool categories, tools within each category and sectorial dimension

СВ	Capital Buffers
CB_OCRTI	Other Capital Requirements Targeting most important Institutions
CB_OCS	Other capital surcharges and own funds requirements
CB_OCS_CRE	Other Capital Surcharges on lending to NFCs for other purposes
CB_OCS_RRE	Other Capital Surcharges on lending to HHs for Residential Real Estate
СВ_ССуВ	Countercyclical Capital Buffer
CB_CCB	Capital Conservation Buffer
CB_SRB	Systemic Risk Buffer
CB_SRB_CRE	Systemic Risk Buffer on lending to NFCs for Commercial Real Estate
CB_OSII	O-SII capital buffer
CB_PDR	Profit Distribution Restrictions
CB_GSII	G-SII Capital Buffer

A.3.1. Capital Buffer MaPPed tool category

A.3.2. Leverage MaPPed tool category

LVR Leverage ratio

A.3.3. Limits of Credit Growth Volume MaPPed tool category

LCGV	Limits on Credit Growth Volume
LCGV_LRR	Liability-based Reserve Requirements
LCGV_ARR	Reserve Requirements based on Assets
LCGV_ARR_CONS	Asset-based Reserve Requirements on lending to HHs for consumption
LCGV_ARR_CRE	Asset-based Reserve Requirements on lending to NFCs for Commercial Real Estate
LCGV_ARR_oNFC	Asset-based Reserve Requirements on lending to NFCs for other purposes
LCGV_ARR_RRE	Asset-based Reserve Requirements on lending to HHs for Residential Real Estate
LCGV_ARR_GOVT	Asset-based Reserve Requirements on lending to Government

A.3.4. Liquidity Restrictions and Limits on Currency and Maturity Mismatch MaPPed tool category

LRLCMM	Liquidity Restrictions and Limits on Currency and Maturity Mismatch
LRLCMM_LTD	Loan-to-Deposit limits
LRLCMM_STLCR	Short Term Liquidity Coverage Ratio
LRLCMM_LRDCR	Liquidity Ratios and Deposit Coverage Ratios
LRLCMM_LFXM	Limits on Foreign Currency Mismatch
LRLCMM_OLR	Other Liquidity Requirements
LRLCMM_OLR_RRE	Other Liquidity Restrictions on lending to HHs for Residential Real Estate
LRLCMM_OSFR	Other Stable Funding Requirements

A.3.5. Tax MaPPed tool category

TAX Tax on assets/liabilities

A.3.6. Minimum Capital Requirements MaPPed tool category

MCR	Minimum Capital Requirements
MCR_CAR	Capital Adequacy Ratio
MCR_T1	Tier1 capital Ratio
MCR_CET1	Common Equity Capital Tier1 Ratio
MCR_CORET1	Core T1 capital Ratio

A.3.7. Loan Loss Provisions MaPPed tool category

LLP	Loan Loss Provisions
LLP_LCR	Loan Classification Rules
LLP_CTLLR	Capital Treatment of Loan Loss Reserve
LLP_MSP	Minimum Specific Provsisioning
LLP_MSP_RRE	Minimum Specific Provsisioning on lending to HHs for Residential Real Estate
LLP_MSP_CONS	Minimum Specific Provsisioning on lending to HHs for consumption
LLP_MSP_CRE	Minimum Specific Provsisioning on lending to NFCs for Commercial Real Estate
LLP_MSP_oNFC	Minimum Specific Provsisioning on lending to NFCs for other purposes
LLP_GP	General Provisioning
LLP_GP_RRE	General Provisioning on lending to HHs for Residential Real Estate
LLP_GP_CONS	General Provisioning on lending to HHs for consumption
LLP_GP_CRE	General Provisioning on lending to NFCs for Commercial Real Estate
LLP_GP_oNFC	General Provisioning on lending to NFCs for other purposes
LLP_GP_GOVT	General Provisioning on lending to Government

A.3.8. Risk Weights MaPPed tool category

RW	Risk Weights
RW_RREa	Risk Weights on loans backed by Residential Real Estate
RW_CREa	Risk Weights on loans backed by Commercial Real Estate
	Risk Weights on loans backed by Comercial Real Estate for lending to NFCs for
RW_CRE_CRE	Comercial Real Estate
	Risk Weights on loans backed by Comercial Real Estate for lending to NFCs for Other
RW_CRE_oNFC	Financial Institutions
RW_OSW	Other Sectoral Risk Weights
RW_OSW_O	Other Sectoral Risk Weights on lending to Other sectors
RW_OSW_FX	Other Sectoral Risk Weights on lending in Foreign Currency
RW_OSW_RRE	Other Sectoral Risk Weights on lending to HHs for Residential Real Estate
RW_OSW_CRE	Other Sectoral Risk Weights on lending to NFCs for Commercial Real Estate
RW_OSW_oNFC	Other Sectoral Risk Weights on lending to NFCs for other purposes
RW_OSW_GOVT	Other Sectoral Risk Weights on lending to Government
RW_OSW_OFI	Other Sectoral Risk Weights on lending to Other Financial Institutions

A.3.9. Lending Standards and Restrictions MaPPed tool category

LSR	Lending Standard Restrictions
LSR_OR	Other Restrictions
LSR_OR_CRE	Other Restrictions on lending to NFCs for Commercial Real Estate
LSR_OR_oNFC	Other Restriction on lending to NFCs for other purposes
LSR_OR_RRE	Other Restrictions on lending to HHs for Residential Real Estate
LSR_OR_CONS	Other Restrictions on lending to HHs for consumption
LSR_OR_OFI	Other Restrictions on lending to Other Financial Institutions
LSR_OR_GOVT	Other Restrictions on lending to Government
LSR_LOI	Limits on Interest Rates on loans
LSR_LOI_CONS	Limits on Interest Rates on lending to HHs for consumption
LSR_LOI_RRE	Limits on Interest Rates on lending to HHs for Residential Real Estate
LSR_LTV	Loan-to-Value limits
LSR_LTV_RRE	Loan-to-Value limits on lending to HHs for Residential Real Estate
LSR_LTV_CONS	Loan-to-Value limits on lending to HHs for consumption
LSR_LTV_CRE	Loan-to-Value limits on lending to NFCs for Commercial Real Estate
LSR_DSTI	Debt-Service-to-Income limits
LSR_DSTI_RRE	Debt-Service-to-Income limits on lending to HHs for Residential Real Estate
LSR_DSTI_CONS	Debt-Service-to-Income limits on lending to HHs for consumption
LSR_DSTI_CRE	Debt-Service-to-Income limits on lending to NFCs for Commercial Real Estate
LSR_MAR	Maturity and Amortisation Restrictions
LSR_MAR_RRE	Maturity and Amortisation Restrictions on lending to HHs for Residential Real Estate
LSR_MAR_CONS	Maturity and Amortisation Restrictions on lending to HHs for consumption
LSR_MAR_CRE	Maturity and Amortisation Restrictions on lending to NFCs for Commercial Real Estate
LSR_MAR_oNFC	Maturity and Amortisation Restrictions on lending to NFCs for other purposes
LSR_OIR	Other Income Requirements for loan eligibility
LSR_OIR_RRE	Other Income Restrictions on lending to HHs for Residential Real Estate
LSR_OIR_CRE	Other Income Restrictions on lending to NFCs for Commercial Real Estate
LSR_OIR_CONS	Other Income Restrictions on lending to HHs for consumption
LSR_LVPL	Limits on the Volume of Personal Loans
LSR_LVPL_CONS	Limits on the Volume of Personal Loans on lending to HHs for consumption
LSR_LVPL_OFI	Limits on the Volume of Personal Loans on lending to Other Financial Institutions
LSR_LTI	Loan-to-Income
LSR_LTI_RRE	Loan-to-Income on lending to HHs for Residential Real Estate

LLEC	Limits on Large Exposures and Concentration
LLEC_SCE	Single Client Exposures limits
LLEC_SCE_OFI	Single Client Exposures limits on lending to Other Financial Institutions
LLEC_SCE_GOVT	Single Client Exposures limits on lending to Government
LLEC_SCE_CRE	Single Client Exposures limits on lending to NFCs for Commercial Real Estate
LLEC_SCE_oNFC	Single Client Exposures limits on lending to NFCs for other purposes
LLEC_SCE_RRE	Single Client Exposures limits on lending to HHs for Residential Real Estate
LLEC_SCE_CONS	Single Client Exposures limits on lending to HHs for consumption
LLEC_IE	Intragroup Exposure limits
LLEC_IE_OFI	Intragroup Exposure limits on lending to Other Financial Institutions
LLEC_IE_RRE	Intragroup Exposure limits on lending to HHs for Residential Real Estate
LLEC_IE_CRE	Intragroup Exposure limits on lending to NFCs for Commercial Real Estate
LLEC_IE_oNFC	Intragroup Exposure limits on lending to NFCs for other purposes
LLEC_QH	Limits on qualified holdings outside the financial-sector
	Limits on qualified holdings outside the financial-sector on lending to NFCs for
LLEC_QH_oNFC	other purposes
	Limits on qualified holdings outside the financial-sector on lending to Other
LLEC_QH_OFI	Financial Institutions
	Limits on qualified holdings outside the financial-sector on lending to NFCs for
	Soctor and Market Sogment Exposure limits
LLEC_SIVISE	Sector and Market Segment Exposure limits on lending to Other Einancial
LLEC SMSE OF	Institutions
	Sector and Market Segment Exposure limits on lending to NFCs for
LLEC_SMSE_CRE	Commercial Real Estate
	Sector and Market Segment Exposure limits on lending to NFCs for other
LLEC_SMSE_oNFC	purposes
LLEC_FC	Funding concentration limits
LLEC_FC_OFI	Funding concentration limits on loans to Other Financial Institutions
LLEC_OECL	Other Exposure and Concentration limits
	Other Exposure and Concentration limits on lending to NFCs for other
LLEC_OECL_oNFC	purposes

A.3.11. Other Measures MaPPed tool category

ОМ	Other Measures
OM_O	Other
OM_O_RRE	Other on lending to HHs for Residential Real Estate
OM_O_oNFC	Other on lending to NFCs for other purposes
OM_LDR	Limits on Deposit Rates
OM_CMT	Crisis Management Tools
OM_SM	Structural Measures
OM_SM_OFI	on lending to Other Financial Institutions
OM_ORR	Other Regulatory Restrictions
OM_ORR_GOVT	Other Regulatory Restrictions on lending to Government
OM_ORR_OFI	Other Regulatory Restrictions on lending to Other Financial Institutions
OM_ORR_RRE	Other Regulatory Restrictions on lending to HHs for Residential Real Estate
OM_MR	Margin Requirements
OM_MR_OFI	Margin Requirements on lending to Other Financial Institutions
OM_MR_oNFC	Margin Requirements on lending to NFCs for other purposes
OM_MR_O	Margin Requirements
OM_DRP	Debt Resolution Policies
OM_DRP_RRE	Debt Resolution Policies on lending to HHs for Residential Real Estate
OM_DRP_CONS	Debt Resolution Policies on lending to HHs for consumption
OM_DRP_CRE	Debt Resolution Policies on lending to NFCs for Commercial Real Estate
OM_DRP_oNFC	Debt Resolution Policies on lending to NFCs for other purposes
OM_CRF	Change in Regulatory Framework

Figure A.2. $MaPP_{TOT}$ index for the remaining EU countries



Figure A.3. MaPP_{dem} and MaPP_{sup} indices of the remaining EU countries



Figure A.4. MaPP_{supLoan}, MaPP_{supCap} and MaPP_{supGen} indices of the remaining EU countries



Figure A.5. $MaPP_{HH}$ and $MaPP_{NFC}$ of the remaining EU countries





Figure A.6. Real interest rates on loans to NFCs and on mortgages for the remaining EU countries

Figure A.7. The YoY growth rate of loans to HHs and our proxy for credit demand from HHs [E(hhDem)]



Figure A.8. The YoY growth rate of loans to NFCs and our proxy for credit demand from NFCs [E(firmDem)]



Figure A.9. Local Projections on ri_NFC_a2z on full sample.



Figure A.10. Local Projections of total, demand- and supply-side MaPP indexes on ri_NFC_a2z on EA countries (top row) and nonEA countries (bottom row)



Figure A.11. Local Projections of the three different supply-side MaPP tools on ri_NFC_a2z for EA countries and nonEA countries.



Figure A.12. Local Projections of total, demand- and supply-side MaPP indexes on ri_mort_o10 on EA countries (top row) and on nonEA countries, ri_mort_1to5 (bottom row)



Figure A.13. Local Projections of the three different supply-side MaPP tools on ri_mort_010 for EA countries and on ri_mort_1to5 for nonEA countries.

