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Contact to corresponding author: Milan Nedeljkovic, mnedeljkovic@fefa.edu.rs

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Jelisaveta Lazarevic

Metropolitan University, Serbia

 orcid.org/0000-0001-6888-5827

Tanja Kuzman


Metropolitan University, Serbia

 orcid.org/0000-0002-8357-3634

Milan Nedeljkovic

Metropolitan University, Serbia

CESifo, Germany

 orcid.org/0000-0002-1773-3054

Credit cycles and macroprudential policies in emerging market economies

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Abstract

Research background: Excessive credit expansions have an important role in the generation and amplification of business cycles in emerging market (EM) economies. Macroprudential policies can be beneficial in restraining excessive credit growth and safeguarding financial stability. Despite recent theoretical advances in understanding of the benefits of macroprudential policies, empirical evidence on their effect on the credit cycle is still scarce.

Purpose of the article: This paper studies the effectiveness of macroprudential measures in the sample of major EM economies focusing on the broad credit measure and using an empirical framework which aims to alleviate several concerns in the previous literature. We examine the effectiveness of four categories of measures which are granular enough to provide relevant policy

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perspectives, whilst mitigating data sparsity issues. By exploiting both time-series and cross-country variation in the tightness of macroprudential regulation in the construction of policy variables we also mitigate some of the common reverse causality concerns.

Methods: We use panel data and employ several (fixed effect, bias corrected LSDV and dynamic interactive fixed effect) estimators to ensure that the results are not sensitive with respect to the estimation method while, together with our construction of the policy variables, alleviating other endogeneity concerns.

Findings & value added: We uncover the heterogeneity in the effects of macroprudential measures on the credit cycle. While measures related to bank capital and credit activity are found to be effective in leaning-against the credit cycle, the measures targeting bank liquidity and FX exposures fail to have statistically significant effect. Our results provide the rationale for mixed evidence in the empirical literature studying the effectiveness of the broadly defined macroprudential measures. From the policy perspective, our findings provide evidence that the measures which address excessive credit expansion and strengthen the resilience of the financial system are effective in the EM economies.

Introduction

Financial factors are important drivers of dynamics of real and financial variables in both advanced and emerging market (EM) economies. Jermann and Quadrini (2012), Chang and Fernandez (2013), Bahadir and Gumus (2016), among others, discussed the role of financial shocks and credit fluctuations in the generation, amplification, and propagation of business cycles. The recent 2007–09 global financial crisis (GFC) further emphasized the role of financial factors, and in particular the credit cycle, in the build-up of the financial crisis and subsequent economic recession (see, e.g., Bernanke, 2018, for an overview of the literature). The link between the credit cycle and the macroeconomic fluctuations, however, is not confined only to the most recent period characterized by the complex innovations in the financial system. Using the long-span data, Schularick and Taylor (2012), Gourinchas and Obsfeld (2012) showed that excessive credit growth emerges as the key predictor of financial crises throughout history.

On those foundations, there is a growing awareness, especially since the beginning of the GFC, that macroprudential policies can play an important role in restraining excessive credit growth and safeguarding financial stability. The need for the implementation of macroprudential policies arises due to the presence of different types of externalities and market failures associated with the behaviour of financial agents (see, e.g., Farhi & Werning, 2016; Bianchi & Mendoza, 2018; Jeanne & Korinek, 2019). For example, “pecuniary externality” (Dávila & Korinek, 2018) implies the situation where higher borrowing by individual agents increases domestic asset prices and reduces collateral constraints in the overall economy and in this way collectively contributes to higher aggregate financial fragility. This happens because individual agents, when making decisions on the borrowing, do not

consider how their actions can influence the asset prices and the borrowing behaviour of other agents, leading up to the overborrowing and the accumulation of risks in the economy. The latter, in turn, can set the seeds of the financial crises and lead to worse economic outcomes. The presence of externalities and market failures implies the role for macroprudential policy in preventing the build-up of systemic risk in the financial system even in situations when other macroeconomic policies are well-tuned. Indeed, a significant number of EM and developed economies have introduced various types of measures over the past two decades, often with different focus and timing.

We are still at the beginning of understanding the effects of the implemented macroprudential measures in EM economies, especially the effectiveness of different types of the implemented measures. The existing cross-country panel studies (e.g. Claessens *et al.*, 2013; Cerutti *et al.*, 2017; Fendoglu, 2017; Akinci & Olmstead-Rumsey, 2018; Morgan *et al.*, 2019; De Schryder & Opitz, 2021) point to overall effectiveness of implemented measures, but the results differ substantially on the question which measures are effective in mitigating unsustainable credit expansions. Similarly, the evidence from micro-level bank/loan studies (Jimenes *et al.*, 2017, Defusco *et al.*, 2020, Ono *et al.*, 2021, Acharya *et al.*, 2020) does not provide a consensus view on the overall effectiveness of the specific measures. The need for better understanding of the measures' effectiveness is especially relevant from the policy perspective in the present stage of the Covid-19 pandemic. The previously implemented abundant liquidity and financial support measures could lead to asset price inflation and build-up of risks which in combination with changes in the investors' sentiment may exert significant pressures on the EM's financial sector and the economies in the future. This requires a careful sequencing of policy measures ensuring robust economic recovery with manageable financial risks.

The primary empirical challenge in cross-country panel studies is the potential endogeneity of the macroprudential variable. The available datasets provide indices of the number of policy actions in each month or a quarter. The studies using within a country change in the macroprudential indices are prone to reverse causality concerns since the policy changes are typically initiated in response to local (current or expected) macroeconomic dynamics. The limited number of policy changes (sparsity over time or between countries) also plagues panel studies focused on specific measures. This paper adds to the literature by empirically studying the relation between credit cycles and macroprudential policies in the sample of EM economies using an empirical framework which aims to alleviate these concerns. Specifically, we use data for sixteen major EM economies at

quarterly frequency between 2000 and 2018, and different (fixed effect, bias-corrected least squares dummy variable (LSDV) and dynamic interactive fixed effect) estimators to examine the effectiveness of four categories of measures (bank capital, credit activity, bank foreign currency (FX) exposures and bank liquidity) which are granular enough to provide relevant policy perspectives, whilst mitigating data sparsity issues. We identify the policy effect using both cross-country and time variation in the level of macroprudential regulation, thereby mitigating reverse causality concerns.

We document three stylized facts. First, in line with the existing literature, we find that macroprudential measures are generally effective in restraining credit cycles in the observed sample of EM economies. Furthermore, we find heterogeneity in the effect of the different types of implemented macroprudential measures. The measures targeting bank capital and credit activity are found to be effective in leaning-against-the credit cycle, contributing to the reduction in excessive credit-to-GDP ratio in the range between 0.4 and 0.6% points. In contrast, bank liquidity measures appear to be only very weakly related to the credit cycle, as the coefficient for this variable is largely insignificant across the specifications. Third, the measures aimed at limiting bank FX exposures do not have a statistically significant effect on the excessive credit growth. The results are not sensitive with respect to the estimation method, included control variables, or with respect to the definition of the dependent variable.

The results provide new empirical evidence on the leaning-against the credit cycle effectiveness of different types of macroprudential measures in EM economies. The results are generally in line with the relatively scarce previous literature which documents the effectiveness of either broadly defined index of macroprudential measures or of the specific types of the measures. Our empirical approach, which balances between the granularity of measures and the sparsity of available policy data, however, sheds new light on somewhat conflicting findings in previous literature. Our finding that only the measures related to bank capital and credit activity are effective in taming the credit cycle can elucidate why combining different types of measures in the construction of the policy variable may provide insignificant estimates. From the policy perspective, our findings provide encouraging evidence that macroprudential measures which are primarily applied to address excessive credit expansion and strengthen the resilience of the financial system are indeed effective in achieving this goal in EM economies.

The paper is organized in the following way. The next section, Section 2 positions the paper with respect to the existing literature and outlines our contributions. Section 3 discusses the data and empirical methodology.

Section 4 presents the empirical results, together with various specification checks. Section 5 discusses the main results, while Section 6 concludes.

Literature review

Despite the fact that the term “macroprudential” has its roots in the 1970s (Galati & Moessner, 2018), the literature has started to develop only after 2000. Early literature (Crockett, 2000; Borio, 2003) primarily took the policy view and focused on the need to strengthen the prevailing prudential frameworks through incorporation of macroprudential elements into the existing regulation. The GFC and more systematic introduction of the macroprudential measures in the policy toolkit worldwide have sparked interest in studying the role and the effectiveness of macroprudential measures in mitigating the risks in the financial system. This has led to growing theoretical and empirical literature. In this section we provide the selective overview of the empirical literature on the effectiveness of macroprudential policies in reducing excessive credit expansions, which is the goal of our paper. For an exhaustive literature review, please see several recent papers (Araujo *et al.*, 2020; Forbes, 2021; Galati & Moessner, 2018) which present other relevant aspects of macroprudential regulation, such as their role in the strengthening of local economy’s resilience to global shocks, the interplay with capital flow management measures or the effects on economic growth.

The country-level panel data studies largely provide evidence in support of the dampening effect of macroprudential measures on credit cycle, albeit with limited consensus on the effectiveness of individual types of measures. Lim *et al.* (2011), in one of the first empirical studies, examined the effects of implementation of different macroprudential measures on credit growth as well as on the strength of correlation between credit and GDP growth in the sample of advanced and EM economies over the 2000–2010 period. Using a conventional dynamic panel setting they showed statistically significant association in the case of credit related macroprudential measures and dynamic provisioning rules. Dell’Arcia *et al.* (2012) in their pooled panel data analysis for advanced and EM economies showed that implemented macroprudential policies can mitigate the frequency of the credit boom events. Claessens *et al.* (2013) using the sample of 48 countries over 2000–2010 period found that credit related measures (borrower-based measures and those targeting the asset side of financial institutions) are associated with lower bank credit growth, while no statistically significant effect is found in the case of bank capital and bank liquidity measures.

More recent panel data literature also reports mixed evidence. Using a conventional dynamic panel framework Cerutti *et al.* (2017) showed that measures targeting borrowers and financial institutions reduce credit growth in an annual data sample of 56 EM economies over 2000–2013 period. Akinci and Olmstead-Rumsey (2018) found similar results for credit related measures in their sample of 57 countries over the same period, but no significant effect for bank capital related measures. Fendoglu (2017) reported different results using quarterly data over the 2000–2013 period for 18 EMs. He showed that borrower based, and, additionally, foreign exchange related measures are effective in smoothing the credit cycle. In contrast, the paper provides mixed evidence on the effectiveness of measures targeting financial institutions. Moreover, Vandebussche *et al.* (2015) did not find significant effect of borrower-based measures on credit growth in the sample of European EM economies, while credit growth limits and capital requirements were found to be effective. Yet, Morgan *et al.* (2019) and Alam *et al.* (2019) documented the importance of specific borrower-based instruments (i.e., LTV and DSTI limits) on taming mortgage credit and credit to household dynamics, respectively.

Most panel studies use within a country (lagged) change in the macroprudential policy index or in individual measures as the primary explanatory variable, the choice potentially sensitive to endogeneity concerns. In addition, the limited number of policy changes (sparsity over time or between countries) plagues panel studies focused on individual measures. De Schryder and Opitz (2021) is the exception which uses narratively constructed measure of macroprudential shocks as the policy variable in the panel of 13 EU countries. They found no statistically significant effect of the constructed shock on the excessive credit dynamics measured by the credit-to-GDP gap.

Micro-level studies, focused on bank and loan-level data generally point to effectiveness of specific macroprudential policies in curbing credit growth, albeit again with some conflicting results. In a path-breaking study with Spanish credit registry data, Jiménez *et al.* (2017) showed that dynamic provisioning can reduce bank lending pro-cyclicality. Aiyar *et al.* (2016) and Basten (2020) using bank/loan level data for the UK and Switzerland, respectively, found that higher capital requirements may slow down credit and mortgage growth. Defusco *et al.* (2020) showed that policies which target household leverage, such as the Dodd–Frank “Ability-to-Repay” rule in the US which increased the cost of originating high-leverage mortgages, can significantly reduce mortgage credit availability. In contrast, using registry data in Japan, Ono *et al.* (2021) showed that caps on LTV ratios of business loans display counter-cyclical behaviour, failing thereby to miti-

gate the credit risk build-up. Moreover, Acharya *et al.* (2020) documented that while introduction of LTV and LTI limits on household mortgages in Ireland cooled down the house price dynamics, this also led banks to increase risk exposure in corporate credits and securities, two assets which were not targeted by the policy change. This arbitrage behavior or the “leakage” of measures (previously empirically studied in e.g. Aiyar *et al.*, 2014; Cizel *et al.*, 2019) implies the need to theoretically study the general equilibrium effects of the introduction of the specific measures. In addition, this implies that empirical understanding of the total effect of the implemented measures on the credit dynamics may require focusing on macroeconomic aggregates.

Our results contribute to the discussion in two main ways. First, our research design provides more homogenous focus to the question of effectiveness along several dimensions. We examine the effectiveness of measures grouped in four categories which are granular enough to provide relevant policy perspectives (bank capital, bank liquidity, FX exposures, credit activity), whilst having sufficient country and time dynamics (changes) in the group measures over the sample that enables identification of the underlying effects. The limited number of changes (sparsity over time or between countries) affects studies focused on individual measures. Our dataset also includes a longer time-span than most studies including the recent period in which macroprudential policies have been more frequently used.

Second, our empirical framework allows alleviating some of the endogeneity concerns that are largely present in the existing literature. The studies which use only within a country change in the macroprudential policy (panel or single country) are prone to reverse causality concerns since the changes in the policy variable are often initiated in response to local macroeconomic dynamics. In contrast, we identify the policy effect using both cross-country and time variation in the level of macroprudential regulation. Our policy variable is defined as the state of tight macroprudential policy and thereby depends only on the relative levels of implemented measures at each point in time. Since the levels are largely predetermined (being the outcomes of policy decisions over the previous periods), whilst the relative changes in levels are driven by full cross-sectional information, the scope for the presence of reverse causality in our framework is much weaker. Furthermore, we control for the presence of unobserved confounding factors which are both cross-section and time varying via estimation of specifications which include interactive fixed effects alleviating further the endogeneity concerns.

Research methods

We study the relationship between credit cycles and macroprudential measures using balanced panel data and employing different (fixed effect, bias-corrected LSDV and dynamic interactive fixed effect) estimators to ensure that the results are not sensitive with respect to the estimation method while also alleviating some of the endogeneity concerns. In the following parts of this section, we discuss the data, construction of policy variables of interest and employed econometric model.

Data

Our sample includes quarterly data over the 2000–2018 period for the credit to the non-financial sector and 17 categories of macroprudential measures, our core variables of interest. In addition, we collect data for a variety of external drivers that might influence credit dynamics (e.g., aggregate demand conditions, balance sheet effects, monetary policy character). Our sample includes sixteen EM economies (Brazil, Chile, China, Colombia, the Czech Republic, Hungary, India, Indonesia, Korea Republic, Malaysia, Mexico, Poland, Russia, South Africa, Thailand, and Turkey). The choice of the economies is based on three criteria: i) the selected economies belong to more advanced group of EM economies, viewed also from the global investors' perspective (please see the latest available MSCI emerging market classification¹); ii) data for the dependent variable, total (broad) credit to the non-financial sector, is available from the single relevant source (Bank for International Settlements, BIS) avoiding potential measurement comparability issues when using data from national sources; iii) the sample is geographically dispersed. The sample time length is determined by the data availability and the fact that the use of macroprudential measures in EM countries primarily began after 2000.

Credit data

The primary source for the credit to the non-financial sector data, at quarterly frequency, is the Bank for International Settlements (BIS) database. The BIS statistic shows the level of lending activity to the non-financial sector from all domestic financial institutions (banks and financial corporations), non-financial corporations and non-residents. Including all lending sources allows us to explicitly take into account the build-up of

¹ <https://www.msci.com/our-solutions/indexes/market-classification>.

excessive credit dynamics beyond what is channelled through the local banks, thereby capturing potential leakages of the specific measures (Cizel *et al.*, 2019). The data is reported as credit to GDP ratio. Following the Basel accord practice and previous literature (see, e.g., Fendoglu, 2017, Araujo *et al.*, 2020, De Schryder & Opitz, 2021), we use “credit gap” that represents deviation of the actual credit to GDP ratio from its long-run value (trend) for the assessment of excessive credit booms. We used one-side recursive Hodrick-Prescott (HP) filter to estimate the trend value of the credit to GDP ratio.² To evaluate the importance of HP filter for the obtained results, we used a cubic-trend time polynomial (Garcia-Cicco *et al.*, 2010) to construct an alternative measure of the trend. Estimated gaps (positive / negative values) imply that credit levels depart from the stable long-run levels.

Macroprudential data

iMaPP database — the IMF’s Integrated Macroprudential Policy database is used as a source for macroprudential data in line with other cross-country studies (Alam *et al.*, 2019, Bergant *et al.*, 2020). The database is the most comprehensive cross-country source of information on micro and macro prudential measures between 1990 and 2018 for seventeen types of measures. For each measure and each month, the number of easing and tightening measures is recorded in the database.

Using the raw data, we construct indices of macroprudential policy actions for four categories of interest — bank capital, credit activity, bank liquidity and bank FX exposures. The categories correspond to key policy dimensions of interest in EM economies and facilitate more granular analysis while controlling for the sparsity in the individual measures’ data. The indices are constructed through the two-stage procedure. In the first stage, for each of 17 measures we sum all reported policy changes within a quarter and construct a quarterly index of net cumulative policy measures. In the second stage, we construct the category level index by summing the net cumulative measures which belong to the given category. In this way, the end results are quarterly indices of net cumulative macroprudential policy stance for each category of interest.

The bank capital category includes the following measures (using the iMaPP nomenclature): changes to capital requirements, countercyclical

² We set $\lambda=25000$ in the calculation of the filter (see, e.g., Baba *et al.*, 2020). The choice of lambda follows empirical literature which shows that financial cycles typically have longer duration compared to the real business cycles (Claessens *et al.*, 2013; Drehmann & Tsatsaronis, 2014).

capital buffer (CCB), capital conservation buffer, leverage limits (LVR), loan loss requirement (including the provisioning) and systemically important financial institutions (SIFI). The credit activity category includes the measures targeting credit supply and demand — caps on loan-to-value (LTV) and debt-service-to-income ratios (DSTI), taxes on transactions (tax), limits on bank credit growth (LCG) and other bank loan restrictions. The bank liquidity category includes changes in the reserved requirements, various liquidity measures (net stable funding and core funding ratios, liquidity coverage ratio, liquid asset ratio and external debt restrictions) and loan-to-deposit ratio (LTD). Finally, the bank FX exposure category looks at the cumulative effect of limits on foreign currency credits, limits on gross open FX positions and reserve requirements on foreign currency assets. Figure 1 highlights that the EM economies increasingly implemented macroprudential measures over the sample. The pace at which the measures were implemented increased more strongly over the post GFC period (since 2010), in line with the increasing recognition of the role policies' role in safeguarding financial stability.

Control variables

To control for the potential confounding effects of a variety of external drivers that might influence credit dynamics (e.g., aggregate demand conditions, balance sheet effects, monetary policy character) we include several covariates. Following the approach of Fendoglu (2017) and De Schryder and Opitz (2021) we use average quarterly (year-on-year, y-o-y) GDP growth and quarterly (y-o-y) inflation as proxies of the aggregate demand condition, the real exchange rate to approximate the balance sheet effects, while the central bank policy rate is used as a proxy of monetary policy stance. We used X-13 ARIMA approach for seasonal adjustments of control variables that displayed seasonality. The descriptive statistics and data source for each variable is outlined in Table 1.

Econometric model

Following the existing panel literature (e.g, Cerutti *et al.*, 2017; Fendoglu, 2017; Akinci & Olmstead-Rumsey, 2018; Morgan *et al.*, 2019) we estimate the following baseline specification:

$$y_{i,t} = \alpha_i + \mu_t + \beta MPP_{i,t-k} + \delta y_{i,t-1} + \Pi X_{i,t-p} + u_{i,t} \quad (1)$$

In the above specification, $i=1..N$ denotes country dimension and $t=1..T$ denotes time. $y_{i,t}$ is the specific credit measure and α_i (μ_t) are country (time) fixed effects. $MPP_{i,t-k}$ is the macroprudential variable described in detail in the following paragraph. The country fixed effects α_i control for country-specific, time-invariant drivers of credit dynamics such as initial economic development, social and legal factors. The time fixed effects μ_t absorb the influence of time varying (global) shocks which impact all countries simultaneously. $X_{i,t-p}$ is the vector of lagged covariates which may impact both the credit cycle and the macroprudential policy measures. The variables enter with lag p to alleviate potential simultaneity bias.

We estimate the specification (1) with four different MPP variables (capital, credit, FX exposure, liquidity). Each $MPP_{i,t-k}$ variable is a dummy variable defined to imply the presence/absence of tight macroprudential framework in the respective dimension in country i , k quarters ago. The variable takes value 1 if the country i at time $t-k$ ranks above the cross-sectional median with respect to the level of macroprudential regulation and zero otherwise (see e.g., Zeev, 2017, for similar construction of policy variables in a different context). The definition of the policy variables in this way enables us to: 1) take into account the fact that net tightening in macroprudential regulation might happen at different pace across countries and over time; 2) minimize the reverse causality concerns as the selection to the state of tight macroprudential policy at time t is driven by the level of implemented measures in all countries at time t . Since the levels are largely predetermined (being the outcomes of policy decisions over the previous periods), whilst the relative changes in levels are driven by full cross-sectional information, the scope for the presence of reverse causality in our framework is much weaker relative to the case when the policy variable is defined as the current change in individual country's policy measures. Using k lags in the construction of the policy variables follows empirical findings (Frost *et al.*, 2020, Bergant *et al.*, 2020, De Schryder & Opitz, 2021) which documented that changes in macroprudential measures do not have immediate impact on the macro aggregates.

The baseline specification is estimated using the standard fixed effect (FE) estimator (Wooldridge, 2010) in line with the relatively long time series dimension of the sample. The inclusion of lagged dependent variable in panels with small to medium-sized time dimensions, however, leads to biasedness and inconsistency of the standard fixed effect estimator. To mitigate these concerns in our moderate-to-large T data framework³, we

³ The bias is vanishing with increasing time dimension of the sample, see Judson and

also used bias-corrected LSDV estimator introduced by Bun and Kiviet (2003). The estimator relies on Kiviet (1995) who derived analytic (higher order) expressions for the small-sample bias of the LSDV (fixed effect) estimator. The bias-corrected LSDV estimator is obtained by subtracting the estimates of the bias terms from the standard FE estimator such that the bias of the resulting estimator is mitigated while the estimator remains efficient. Indeed, the simulation results in Bun and Kiviet (2003) and Bruno (2005) show that the proposed estimator outperforms alternatives in samples with moderate cross-section and time dimension. In addition, we also estimated alternative specification (2) that includes interactive fixed effects (IFE) $v_{i,t}$ (see, e.g., Moon & Weidner, 2017).

$$y_{i,t} = v_{i,t} + \beta MPP_{i,t-k} + \delta y_{i,t-1} + \Pi X_{i,t-p} + u_{i,t} \tag{2}$$

$$v_{i,t} = \lambda_i f_t$$

The notation in equation (2) remains the same as in (1), the only exception being the interactive fixed effects $v_{i,t}$ which are both country and time varying. The IFE are modelled using the factor model specification $v_{i,t} = \lambda_i f_t$ where unobservable common shocks f_t are allowed to have potentially different (unobserved) country-specific effects λ_i . In this way, the IFE absorb all country and time varying unobserved variation that is potentially correlated with the policy variables and impacting the credit gap. Hence, the obtained estimates are less prone to the potential presence of the omitted variable bias. The standard FE estimator arises as the special case of IFE.

Results

Baseline specification

This section reports the results from the baseline estimates. Dependent variable in all regressions in this section is the credit gap calculated using the recursive HP trend. Following the empirical literature on dynamic effectiveness of macroprudential measures (Fendoglu, 2017; Bergant *et al.*, 2020), we use one lag ($k=1$) in the definition of the policy measures $MPP_{i,t-k}$. We use Driscoll and Kraay (1998) standard errors to control for the potential spatial and serial correlation in error terms. Table 2 presents

Owen (1999) for Monte Carlo analysis.

the baseline estimates for macroprudential measures of interest — capital (Column 1 and 2), credit (Column 3 and 4), FX exposure (Column 5 and 6) and liquidity (Column 7 and 8).

The obtained results reveal heterogeneity in the response of the credit cycle to different policy measures. Tightening of macroprudential policy measures related to bank capital is negatively associated with the credit cycle. The estimated effect is statistically significant and ranges between -0.55% and -0.61% of GDP at the quarterly frequency, depending on whether the time effects are included in the specification. The finding is in line with Vandebussche *et al.* (2015) and Cerutti *et al.* (2017) who document that tightening of capital related measures is negatively associated with household and bank credit growth in EM economies, respectively. Our estimates which focus on total lending activity in the economy imply that higher capital requirements, stricter loan loss requirements and changes in CCB also contribute to reduction of overall excess credit dynamics in EM economies.

Furthermore, we find statistically significant negative effect of credit related macroprudential measures on the credit gap. The estimated effect is similar in magnitude to the effect of bank capital measures and ranges between -0.64% and -0.48% of GDP. The finding is in line with Cerutti *et al.* (2017), Fendoglu (2017), Akinci and Olmstead-Rumsey (2018) and Morgan *et al.* (2019) who all find negative effects of the tightening of measures which target credit supply and demand on bank and mortgage credit. Our estimates suggest that despite potential leakages the implemented measures do contribute to smoothing of the aggregate credit cycle.

In contrast, we find limited evidence in favour of the effect of bank liquidity measures on the credit cycle as the estimated coefficient fails to be significant when time effects are included in the specification. Finally, we do not find any effect of the limits on the FX exposures on the credit cycle in our EM sample.

The results in Table 2 also show that all control variables enter the specifications with the expected estimated signs. Booming aggregate demand conditions and appreciation of the real exchange rate have positive and statistically significant association with credit gap. The effect of the change in short term policy rate is somewhat mixed with estimated coefficient that is statistically insignificant.

Specification checks

We put baseline specification through various specification checks. Firstly, we employ alternative bias-corrected LSDV estimator of specifica-

tion (1). We used clustered bootstrap with 500 repetitions to estimate the standard errors. The results (Table 3) remain robust and quantitatively similar when compared to the baseline estimates confirming that only capital- and credit-related macroprudential measures are efficient in leaning-against the credit cycles.

Secondly, we estimate alternative specification (2) using a bias-corrected version of the dynamic IFE estimator that accounts for time-serial correlation and time and cross-sectional heteroscedasticity in the error term (see, Moon & Weidner, 2017). Since the interactive effects absorb time variation and country fixed effect, in Table 4 we do not report different specification with or without time fixed effects. The estimated coefficients are yet again qualitatively and quantitatively analogous to the baseline estimates.

Further, we evaluate the sensitivity of our results to the changes of dependent, policy and control variables. Tables 5-8 report the obtained estimates separately for each policy measure. In each table we repeat the baseline estimate (Column 1) and provide estimates with alternative dependent variable — credit gap based on the cubic time polynomial estimates of the trend (Column 2) and y-on-y credit growth (Column 3). We also estimate the relation of interest at alternative lags of 2 and 4 quarters (Columns 4 and 5) to capture potential lagged effects in the transmission of macroprudential policy measures. Finally, we use alternative control variables in our main specification: lagged y-on-y GDP growth (Column 6); lagged y-on-y change in the real exchange rate (Column 7) and lagged average quarterly change in the central bank policy rate (Column 8).

Table 5 presents the results for the bank capital related measures. The sign and significance of alternative estimates confirms the counter-cyclical impact of the tightening of the capital related macroprudential measures on the credit gap. This result is irrespective of: 1) the way in which the dependent variables are constructed; 2) the time horizon at which the effect is evaluated; and 3) the included control variable set.

Table 6 presents the sensitivity checks for the specification which focuses on the macroprudential measures related to the credit activity. The estimates confirm the negative association of tightening credit measures and credit gap independently from the way in which credit gap is defined (Columns 1–3). Further, they remain robust, with same sign and significance, across the checks with different control variables and lagged effects of credit-related macroprudential measures (Columns 4–8).

Next, using the same approach, we re-run our baseline specification with the focus on FX exposure macroprudential policies (Table 7). The

results remain quantitatively and qualitatively similar to our baseline estimates.

Final specification check replicates the estimations focusing on macroprudential liquidity measures (Table 8). Yet again, the results imply that liquidity measures do not have counter-effects on the credit gap, independently from the way in which the gap is defined, time horizons at which the effect is estimated or using alternative control variables.

To conclude, the estimates from multiple specification checks confirm the insensitivity of our results to the use of alternative estimation methods, several definitions of credit gap, different estimation time horizons, and alternative definitions of control variables. Moreover, dampening effects of different types of macroprudential regulation appear robust in all specification checks.

Discussion

Our results provide new empirical evidence on the leaning-against-the-credit cycle effectiveness of different types of macroprudential measures in EM economies. We show that not all measures targeting financial institutions are equally effective in taming the aggregate credit cycle.

In particular, we find that measures related to bank capital appear to be effective in the sample of EM economies. The result is generally in line with Vandebussche *et al.* (2015) and Cerutti *et al.* (2017) who showed negative association between tightening of bank capital measures and household and bank credit growth in EM economies. Our results show that their finding remains to hold in our empirical framework which tackles endogeneity concerns. Tightening of capital related measures increases banks' cost of funding, reduces profitability and/or limits internal capital generation thereby constraining the banks' credit expansion. The measures may be ineffective in situations when the local banks have access to alternative sources of funding or when they are well capitalized. Both situations are more prevalent in advanced economies compared to EM. This can also potentially explain the difference between our results and Akinci and Olmstead-Rumsey (2018) and De Schryder and Opitz (2021) who focused on both advanced and EM economies and advanced economies only, respectively, and found limiting results in support of the effectiveness of this type of measures. Our results differ from limiting evidence in support of the capital related measures' effectiveness in EM economies in Fendoglu (2017), which can be related to the differences in our empirical approaches.

Our finding of statistically significant negative effect of credit related macroprudential measures on the credit gap is in line with the majority of the previous literature which focuses on bank or mortgage credit growth (Cerutti *et al.*, 2017; Fendoglu, 2017; Akinci & Olmstead-Rumsey, 2018; Morgan *et al.*, 2019, de Araujo *et al.*, 2020). Our results extend their findings by showing that the measures are effective in smoothing total lending activity beyond what is generated by the local banking system. This implies that the “leakages” of this type of measures, studied primarily for advanced economies by Aiyar *et al.* (2014) and Cizel *et al.* (2019), may not be as strong in the case of EM economies.

The lack of statistically significant effect of liquidity and FX exposure focused macroprudential measures on the credit cycle that we obtained corresponds to evidence for the specific components of these measures in Akinci and Olmstead-Rumsey (2018). It differs from Cerutti *et al.* (2017) and Fendoglu (2017) who find that limits on foreign currency positions, changes in reserve requirements and limits on foreign currency credits are associated with lower bank credit growth. Since these measures are primarily targeting banks’ foreign currency domestic lending, they may be circumvented by the borrowers’ direct access to alternative funding sources, including the cross-border lending. Our evidence that measures are not effective in smoothing the total lending cycle thus may signal the presence of this type of leakages, at least in our sample of EM economies.

From the policy perspective, our findings provide encouraging evidence that the measures which are primarily applied to address excessive credit expansion and strengthen the resilience of the financial system, such as changes in the availability of or eligibility for credit instruments as well as adjustments in the quantity and/or quality of capital held by financial institutions, are indeed effective in achieving this goal in EM economies. This may be especially relevant in the current post-pandemic phase when after temporary relaxation of macroprudential measures and introduction of abundant liquidity and financial support programmes (Edwards, 2021), the EM economies are facing strong aggregate demand pressures. This requires a careful sequencing of policy measures ensuring robust economic recovery with manageable financial risks. Moreover, our finding of the lack of statistically significant effect of liquidity and FX exposure focused macroprudential measures on the credit cycle does not invalidate their use in the policy toolkit. The mandate of macroprudential policy goes beyond prevention of excessive credit movements and includes (International Monetary Fund, 2014; Forbes, 2021) addressing and circumventing the systemic risk amplification mechanisms and reducing other structural vulnerabilities in the financial market (such as excessive foreign exchange exposure or liabil-

ity dollarization in EM economies). It is precisely the measures that we find insignificant in driving the credit dynamics which play an important role in achieving these goals.

Conclusions

Excessive credit expansions have an important role in the generation, amplification, and propagation of business cycles in EM economies, including the build-up of financial crises. Active use of macroprudential policies in these economies has a potential to reduce the financial imbalances and enable smoothing of the effect of credit cycle on the real economy. The theoretical literature which developed over the previous decade establishes that introduction of macroprudential tools (typically modelled as a Pigouvian tax) is sufficient to mitigate the externality effects and different market failures and produce efficient equilibrium for the economy. However, the empirical evidence on the effectiveness of macroprudential measures in leaning-against the cycle is still scarce.

This paper contributes to the literature by studying the effectiveness of four types of macroprudential measures in the sample of EM economies in an empirical framework which aims to alleviate several concerns in the previous literature. We examine the effectiveness of measures grouped in four categories which are granular enough to provide relevant policy perspectives (bank capital, bank liquidity, FX exposures, credit activity), whilst mitigating the issue of data sparsity. We exploit both time-series and cross-country variation in the tightness of macroprudential regulation in the construction of policy variables and we use a variety of econometric methods, thus alleviating some of the common endogeneity concerns.

Our findings confirm the general effectiveness of macroprudential measures in containing credit cycles in the EM economies. What is more, we highlight the differences in the effects of different macroprudential measures on the credit cycle. While measures related to bank capital and credit activity are strongly associated with the smoothing of the credit cycle, the measures targeting bank liquidity and FX exposures are found not to be statistically significant. Our results thus provide rationale for mixed evidence on the effectiveness of the broadly defined macroprudential measures which include several different types. From the policy perspective, our findings provide encouraging evidence that the measures which are primarily applied to address excessive credit expansion and strengthen the resilience of the financial system are indeed effective in achieving this goal in EM economies.

Our results should be viewed with the following caveats. While our construction of policy variable circumvents reverse causality concerns, the obtained measure, similar to previous panel studies, captures direction of the policy change (tightening/easing), but not the intensity of the change. Hence, we can measure the effectiveness of tightening actions as such, but our results do not indicate by how much the policy should be tightened. Capturing the policy intensity effects requires construction of new cross-country datasets from the available raw country level data. In addition, our results do not examine any potential asymmetries in the policy effectiveness, which may be potentially conditional on the phase of the credit cycle.

The presented results can also be extended in various ways. In this paper we studied the direct link between the macroprudential measures and the credit cycle. Examining the conditionality in the association between the measures and the credit cycle provides a fruitful avenue to explore. The conditionality may be related to the depth of the financial system, the institutional quality, or other relevant factors. In this way inclusion of more heterogeneous panel structure (advanced and EM economies, EM and developing economies) becomes a viable option given that country heterogeneity can be captured by the conditional relations. Furthermore, the conditional analysis can also shed light on other important aspects of the macroprudential regulation — the effects on economic growth, the role in dampening the effects of global shocks on GDP growth or its importance for weakening the association between capital flows liberalization and systemic risk build-up.

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Annex

Table 1. Descriptive statistics

| Variables | mean | st. dev | Obs | Sources |
|---|-------|---------|------|--------------------------------------|
| Dependent variables | | | | |
| Credit gap (based on HP filter) | 0 | 6.12 | 1088 | BIS |
| Credit gap (based on cubic polynomial) | 0 | 5.69 | 1088 | BIS |
| Credit growth | 2.80 | 7.31 | 1088 | BIS |
| Underlying policy variable | | | | |
| Macroprudential policy: Capital | 2.62 | 3.42 | 1088 | IMF, iMaPP |
| Macroprudential policy: Credit activity | 2.67 | 4.52 | 1088 | IMF, iMaPP |
| Macroprudential policy: FX exposure | 0.76 | 1.57 | 1088 | IMF, iMaPP |
| Macroprudential policy: Liquidity | 0.93 | 1.96 | 1088 | IMF, iMaPP |
| Control variables | | | | |
| Inflation (yoy): change | -0.07 | 1.59 | 1088 | IMF: IFS |
| GDP growth (yoy, 2 year average) | 4.03 | 2.74 | 1088 | IMF: IFS; Chang <i>et al</i> (2015) |
| GDP growth (yoy) | 4.03 | 3.67 | 1088 | IMF: IFS ; Chang <i>et al</i> (2015) |
| Real exchange rate (period end, log) | 4.52 | 0.14 | 1088 | BIS |
| Real exchange rate (period end, yoy) | 0.37 | 8.08 | 1088 | BIS |
| Central bank policy rate (period end, change) | 6.43 | 5.41 | 1088 | BIS |
| Central bank policy rate (period average, change) | 6.46 | 5.47 | 1088 | BIS |

Notes: Names of the variables used in empirical estimations, number of observations and source of data is reported in the Table. The observations belong to 2000Q1-2018Q4. The Table is divided in three panels that report summary statistics for: 1) different measures of dependent variables; 2) policy variables as discussed in Section 3.1; 3) control variables. The dependent variable represents deviation of credit to GDP ratio from its long-term trend, while approximation of the trend is done using HP filter and cubic polynomial. The macroprudential policy variables are indexes of the cumulative sum of net tightening policies, within quarters, related to capital, credit activity, FX exposure and liquidity. For control variables the following applies: 1) yoy is a difference comparison to the same quarter of the previous year; 2) change is the difference between consecutive quarters; 3) two-year average is the rolling average of past eight months; 4) period end is the value recorded at the end of the quarter; 5) period average is computed as average of within quarter values.

Table 2. Baseline specification estimates

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---------------------|---------------------|----------------------|----------------------|---------------------|---------------------|---------------------|---------------------|
| Credit gap (lagged) | 0.870*** (0.020) | 0.846*** (0.022) | 0.872*** (0.019) | 0.847*** (0.022) | 0.873*** (0.020) | 0.850*** (0.022) | 0.871*** (0.020) | 0.848*** (0.022) |
| Inflation (yoy, lagged change) | 0.071** (0.032) | 0.053* (0.028) | 0.068** (0.031) | 0.047* (0.028) | 0.064** (0.032) | 0.047* (0.028) | 0.072** (0.031) | 0.050* (0.027) |
| GDP growth (yoy, 2-year average, lagged) | 0.173*** (0.034) | 0.136*** (0.030) | 0.174*** (0.032) | 0.153*** (0.025) | 0.178*** (0.034) | 0.144*** (0.026) | 0.173*** (0.032) | 0.150*** (0.026) |
| Real exchange rate (period end, log & lagged) | 3.787*** (0.747) | 3.585*** (0.825) | 3.724*** (0.688) | 3.382*** (0.775) | 3.674*** (0.726) | 3.424*** (0.795) | 3.611*** (0.731) | 3.403*** (0.793) |
| Policy rate (period end, lagged change) | 0.022 (0.022) | -0.011 (0.025) | 0.024 (0.020) | 0.003 (0.024) | 0.032 (0.020) | 0.002 (0.024) | 0.02 (0.021) | -0.002 (0.024) |
| Capital (lagged 1 period) | -0.546** (0.247) | -0.613** (0.245) | | | | | | |
| Credit (lagged 1 period) | | | -0.642*** (0.216) | -0.483*** (0.174) | | | | |
| FX exposure (lagged 1 period) | | | | | -0.096 (0.215) | 0.031 (0.229) | | |
| Liquidity (lagged 1 period) | | | | | | | -0.449** (0.216) | -0.233 (0.252) |
| Year effects | No | Yes | No | Yes | No | Yes | No | Yes |
| R ² | 0.8 | 0.81 | 0.8 | 0.81 | 0.8 | 0.81 | 0.8 | 0.81 |
| Observations | 1 088 | 1 088 | 1 088 | 1 088 | 1 088 | 1 088 | 1 088 | 1 088 |

Notes: The Table reports results of the estimation with standard fixed effect estimator. Values in parentheses show Driscoll and Kraay (1998) standard errors. *, ** and *** denote statistical significance at 10%, 5% and 1% level. In all regressions, the dependent variable is lagged credit gap that represents the deviation of credit-to-GDP ratio from the long-run trend estimated using recursive HP filter. Macroeprudential policy variables (Capital, Credit, FX exposure, Liquidity) are dummy variables denoting presence of tight macroprudential regulation. Regressions include country fixed effects, and all variables are constructed in accordance with the discussion provided in the main text. *

Table 3. Estimates using bias-corrected least square dummy variable (LSDV) estimates

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| Credit gap (lagged) | 0.906*** (0.016) | 0.886*** (0.017) | 0.908*** (0.016) | 0.887*** (0.017) | 0.910*** (0.016) | 0.890*** (0.017) | 0.907*** (0.016) | 0.888*** (0.017) |
| Inflation (yoy, lagged change) | 0.069 (0.050) | 0.052 (0.051) | 0.065 (0.050) | 0.046 (0.052) | 0.062 (0.050) | 0.047 (0.052) | 0.070 (0.051) | 0.049 (0.052) |
| GDP growth (yoy, 2-year average, lagged) | 0.162*** (0.040) | 0.127** (0.050) | 0.163*** (0.040) | 0.145*** (0.050) | 0.168*** (0.040) | 0.136*** (0.051) | 0.163*** (0.040) | 0.142*** (0.050) |
| Real exchange rate (period end, log & lagged) | 3.673*** (0.815) | 3.603*** (0.879) | 3.625*** (0.802) | 3.423*** (0.866) | 3.593*** (0.808) | 3.469*** (0.878) | 3.511*** (0.818) | 3.447*** (0.887) |
| Policy rate (period end, lagged change) | 0.025 (0.026) | -0.009 (0.029) | 0.027 (0.027) | 0.005 (0.029) | 0.034 (0.027) | 0.004 (0.029) | 0.022 (0.030) | -0.000 (0.031) |
| Capital (lagged 1 period) | -0.471** (0.236) | -0.543** (0.246) | | | | | | |
| Credit (lagged 1 period) | | | -0.606** (0.264) | -0.446* (0.267) | | | | |
| FX exposure (lagged 1 period) | | | | | -0.109 (0.268) | 0.031 (0.291) | | |
| Liquidity (lagged 1 period) | | | | | | | -0.414 (0.321) | -0.214 (0.357) |
| Year effects | No | Yes | No | Yes | No | Yes | No | Yes |
| Observations | 1 072 | 1 072 | 1 072 | 1 072 | 1 072 | 1 072 | 1 072 | 1 072 |

Notes: The Table reports results of the estimation with bias-corrected LSDV estimator. Values in parentheses show clustered bootstrap standard errors. *, **, and *** denote statistical significance at 10%, 5% and 1% level. In all regressions, the dependent variable is lagged credit gap that represents the deviation of credit-to-GDP ratio from the long-run trend estimated using recursive HP filter. Macroeprudential policy variables (Capital, Credit, FX exposure, Liquidity) are dummy variables denoting presence of tight macroprudential regulation. Regressions include country fixed effects, and all variables are constructed in accordance with the discussion provided in the main text.

Table 4. Estimates using the dynamic interactive fixed effect estimator

| Variable | 1 | 2 | 3 | 4 |
|---|---------------------|---------------------|---------------------|---------------------|
| Credit gap (lagged) | 0.864*** (0.023) | 0.865*** (0.022) | 0.868*** (0.022) | 0.867*** (0.022) |
| Inflation (yoy, lagged change) | 0.038 (0.039) | 0.034 (0.040) | 0.034 (0.040) | 0.035 (0.040) |
| GDP growth (yoy, 2-year average, lagged) | 0.105** (0.043) | 0.123*** (0.044) | 0.113** (0.045) | 0.117** (0.045) |
| Real exchange rate (period end, log & lagged) | 2.861*** (0.783) | 2.760*** (0.777) | 2.759*** (0.780) | 2.773*** (0.777) |
| Policy rate (period end, lagged change) | -0.024 (0.019) | -0.011 (0.020) | -0.012 (0.020) | -0.013 (0.020) |
| Capital (lagged 1 period) | -0.529** (0.223) | | | |
| Credit (lagged 1 period) | | -0.405* (0.237) | | |
| FX exposure (lagged 1 period) | | | 0.033 (0.242) | |
| Liquidity (lagged 1 period) | | | | -0.091 (0.288) |
| Year effects | No | No | No | No |
| Observations | 1 088 | 1 088 | 1 088 | 1 088 |

Notes: The Table reports results of the estimation with bias-corrected IFE estimator. Values in parentheses show standard errors that are robust to time-serial correlation and time and cross-sectional heteroscedasticity in the error term. *, ** and *** denote statistical significance at 10%, 5% and 1% level. In all regressions, the dependent variable is lagged credit gap that represents the deviation of credit-to-GDP ratio from the long-run trend estimated using recursive HP filter. Macroprudential policy variables (Capital, Credit, FX exposure, Liquidity) are dummy variables denoting presence of tight macroprudential regulation. All variables are constructed in accordance with the discussion provided in the main text.

Table 5. Estimates for bank capital related macroprudential measures: alternative lags (2 and 4 quarters) and alternative measures of dependent / control variables

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---------------------|---------------------|---------------------|----------------------|----------------------|---------------------|---------------------|---------------------|
| Credit gap (lagged) | 0.846*** (0.022) | | | 0.846*** (0.022) | 0.845*** (0.022) | 0.850*** (0.022) | 0.855*** (0.022) | 0.846*** (0.022) |
| Inflation (yoy, lagged change) | 0.053* (0.028) | 0.067*** (0.019) | 0.242*** (0.051) | 0.051* (0.027) | 0.053* (0.027) | 0.061** (0.030) | 0.050* (0.027) | 0.053* (0.028) |
| GDP growth (yoy, 2-year average, lagged) | 0.136*** (0.030) | 0.115*** (0.037) | 0.179** (0.080) | 0.136*** (0.029) | 0.135*** (0.028) | 0.135*** (0.028) | 0.119*** (0.028) | 0.137*** (0.030) |
| Real exchange rate (period end, log & lagged) | 3.585*** (0.825) | 2.894*** (0.837) | 6.935*** (1.007) | 3.546*** (0.826) | 3.444*** (0.806) | 3.514*** (0.874) | | 3.605*** (0.821) |
| Policy rate (period end, lagged change) | -0.011 (0.025) | -0.039 (0.026) | -0.151 (0.103) | -0.010 (0.025) | -0.008 (0.025) | -0.016 (0.025) | -0.035* (0.021) | |
| Capital (lagged 1 period) | -0.613** (0.245) | -0.359** (0.163) | -0.840** (0.411) | | | -0.615** (0.251) | -0.535** (0.241) | -0.610** (0.245) |
| Credit gap (cubic, lagged) | | 0.949*** (0.027) | | | | | | |
| Credit growth (yoy, lagged) | | | 0.805*** (0.023) | | | | | |
| Capital (lagged 2 periods) | | | | -0.566*** (0.186) | | | | |
| Capital (lagged 4 periods) | | | | | -0.580*** (0.195) | | | |
| GDP growth (yoy, lagged) | | | | | | 0.050** (0.023) | | |
| Real exchange rate (period end, yoy, lagged) | | | | | | | 0.035*** (0.009) | |
| Policy rate (period average, lagged change) | | | | | | | | -0.009 (0.025) |

Table 5. Continued

| Variable | 1 | | 2 | | 3 | | 4 | | 5 | | 6 | | 7 | | 8 | | |
|----------------|-------|--|-------|--|-------|--|-------|--|-------|--|-------|--|-------|--|-------|--|-------|
| | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | | |
| Year effects | | | | | | | | | | | | | | | | | |
| R ² | 0.81 | | 0.89 | | 0.75 | | 0.81 | | 0.81 | | 0.81 | | 0.81 | | 0.81 | | 0.81 |
| Observations | 1 088 | | 1 088 | | 1 088 | | 1 088 | | 1 088 | | 1 088 | | 1 088 | | 1 088 | | 1 088 |

Notes: The Table reports results of the estimation with standard fixed effect estimator. Values in parentheses show Driscoll and Kraay (1998) standard errors. *, **, and *** denote statistical significance at 10%, 5% and 1% level. Column 1 and Columns 4-8 dependent variable is lagged credit gap that represents the deviation of credit-to-GDP ratio from the long-run trend estimated using recursive HP filter. Column 2 dependent variable is lagged credit gap that represents the deviation of credit-to-GDP ratio from the long-run trend estimated using cubic time polynomial. Column 3 dependent variable is yoy growth of credit. Capital is a dummy variable for the presence/absence of the tight macroprudential regulation with respect to the bank capital. Regressions include country fixed effects, and all variables are constructed in accordance with the discussion provided in the main text. In Column 4, two-quarters policy lags and in Column 5, four-quarter policy lags are reported. Alternative definitions of control variables in covariates are used in Column 6 (GDP growth), Column 7 (real exchange rate) and Column 8 (central bank policy rates).

Table 6. Continued

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|----------------|-------|-------|-------|-------|-------|-------|-------|-------|
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| R ² | 0.81 | 0.89 | 0.75 | 0.81 | 0.81 | 0.81 | 0.81 | 0.81 |
| Observations | 1 088 | 1 088 | 1 088 | 1 088 | 1 088 | 1 088 | 1 088 | 1 088 |

Notes: The Table reports results of the estimation with standard fixed effect estimator. Values in parentheses show Driscoll and Kraay (1998) standard errors. *, **, and *** denote statistical significance at 10%, 5% and 1% level. Column 1 and Columns 4-8 dependent variable is lagged credit gap that represents the deviation of credit-to-GDP ratio from the long-run trend estimated using recursive HP filter. Column 2 dependent variable is lagged credit gap that represents the deviation of credit-to-GDP ratio from the long-run trend estimated using cubic time polynomial. Column 3 dependent variable is yoy growth of credit. Credit is a dummy variable for presence/absence of the tight macroprudential regulation with respect to the bank credit activity. Regressions include country fixed effects, and all variables are constructed in accordance with the discussion provided in the main text. In Column 4, two-quarters policy lags and in Column 5, four-quarter policy lags are reported. Alternative definitions of control variables in covariates are used in Column 6 (GDP growth), Column 7 (real exchange rate) and Column 8 (central bank policy rates).

Table 7. Estimates for FX exposure related macroprudential measure: alternative lags (2 and 4 quarters) and alternative measures of dependent / control variables

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| Credit gap (lagged) | 0.850*** (0.022) | | | 0.850*** (0.022) | 0.849*** (0.022) | 0.854*** (0.022) | 0.857*** (0.023) | 0.850*** (0.022) |
| Inflation (yoy, lagged change) | 0.047* (0.028) | 0.064*** (0.018) | 0.236*** (0.052) | 0.048* (0.028) | 0.045 (0.029) | 0.056* (0.031) | 0.045* (0.027) | 0.047* (0.028) |
| GDP growth (yoy, 2-year average, lagged) | 0.144*** (0.026) | 0.117*** (0.035) | 0.189*** (0.081) | 0.144*** (0.027) | 0.151*** (0.029) | | 0.128*** (0.024) | 0.145*** (0.026) |
| Real exchange rate (period end, log & lagged) | 3.424*** (0.795) | 2.798*** (0.834) | 6.726*** (0.961) | 3.423*** (0.798) | 3.441*** (0.802) | 3.355*** (0.837) | | 3.436*** (0.793) |
| Policy rate (period end, lagged change) | 0.002 (0.024) | -0.031 (0.025) | -0.132 (0.100) | 0.002 (0.024) | 0.001 (0.024) | -0.003 (0.024) | -0.023 (0.019) | |
| FX exposure (lagged 1 period) | 0.031 (0.229) | 0.083 (0.299) | 0.080 (0.419) | | | 0.101 (0.234) | -0.034 (0.253) | 0.031 (0.229) |
| Credit gap (cubic, lagged) | | 0.948*** (0.027) | | | | | | |
| Credit gap (yoy, lagged) | | | 0.806*** (0.023) | | | | | |
| FX exposure (lagged 2 periods) | | | | 0.050 (0.246) | | | | |
| FX exposure (lagged 4 periods) | | | | | -0.138 (0.247) | | | |
| GDP growth (yoy, lagged) | | | | | | 0.058*** (0.021) | | |
| Real exchange rate (period end, yoy, lagged) | | | | | | | 0.035*** (0.009) | |
| Policy rate (period average, lagged change) | | | | | | | | 0.004 (0.024) |

Table 7. Continued

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|----------------|-------|-------|-------|-------|-------|-------|-------|-------|
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| R ² | 0.81 | 0.89 | 0.75 | 0.81 | 0.81 | 0.81 | 0.81 | 0.81 |
| Observations | 1 088 | 1 088 | 1 088 | 1 088 | 1 088 | 1 088 | 1 088 | 1 088 |

Notes: The Table reports results of the estimation with standard fixed effect estimator. Values in parentheses show Driscoll and Kraay (1998) standard errors. *, **, and *** denote statistical significance at 10%, 5% and 1% level. Column 1 and Columns 4-8 dependent variable is lagged credit gap that represents the deviation of credit-to-GDP ratio from the long-run trend estimated using recursive HP filter. Column 2 dependent variable is lagged credit gap that represents the deviation of credit-to-GDP ratio from the long-run trend estimated using cubic time polynomial. Column 3 dependent variable is yoy growth of credit. FX exposure is a dummy variable for presence/absence of the tight macroprudential regulation with respect to the bank FX exposure. Regressions include country fixed effects, and all variables are constructed in accordance with the discussion provided in the main text. In Column 4, two-quarters policy lags and in Column 5, four-quarter policy lags are reported. Alternative definitions of control variables in covariates are used in Column 6 (GDP growth), Column 7 (real exchange rate) and Column 8 (central bank policy rates).

Table 8. Estimates for liquidity related macroprudential measure: alternative lags (2 and 4 quarters) and alternative measures of dependent / control variables

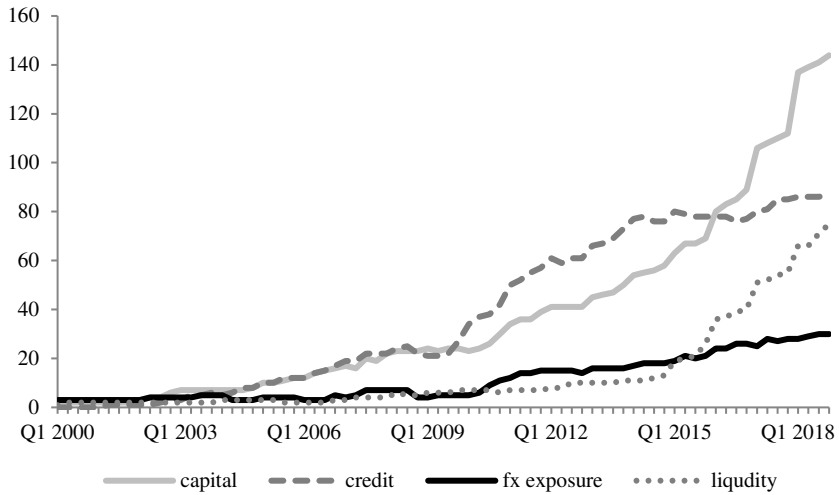
| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| Credit gap (lagged) | 0.848*** (0.022) | | | 0.848*** (0.022) | 0.848*** (0.022) | 0.853*** (0.022) | 0.856*** (0.022) | 0.848*** (0.022) |
| Inflation (yoy, lagged change) | 0.050* (0.027) | 0.063*** (0.019) | 0.245*** (0.053) | 0.050* (0.027) | 0.051* (0.028) | 0.057* (0.030) | 0.048* (0.026) | 0.049* (0.027) |
| GDP growth (yoy, 2-year average, lagged) | 0.150*** (0.026) | 0.120*** (0.035) | 0.211*** (0.080) | 0.151*** (0.026) | 0.154*** (0.024) | | 0.132*** (0.025) | 0.151*** (0.025) |
| Real exchange rate (period end, log & lagged) | 3.403*** (0.793) | 2.796*** (0.822) | 6.628*** (0.947) | 3.400*** (0.790) | 3.359*** (0.781) | 3.341*** (0.830) | | 3.418*** (0.791) |
| Policy rate (period end, lagged change) | -0.002 (0.024) | -0.031 (0.024) | -0.149 (0.100) | -0.003 (0.024) | -0.007 (0.023) | -0.005 (0.024) | -0.027 (0.020) | |
| Liquidity (lagged 1 period) | -0.233 (0.252) | -0.004 (0.246) | -0.950 (0.603) | | | -0.136 (0.260) | -0.251 (0.254) | -0.228 (0.253) |
| Credit gap (cubic, lagged) | | 0.948*** (0.027) | | | | | | |
| Credit growth (yoy, lagged) | | | 0.803*** (0.023) | | | | | |
| Liquidity (lagged 2 periods) | | | | -0.268 (0.269) | | | | |
| Liquidity (lagged 4 periods) | | | | | -0.448 (0.277) | | | |
| GDP growth (yoy, lagged) | | | | | | 0.060*** (0.022) | | |
| Real exchange rate (period end, yoy, lagged) | | | | | | | 0.035*** (0.009) | |
| Policy rate (period average, lagged change) | | | | | | | | -0.000 (0.024) |

Table 8. Continued

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|----------------|-------|-------|-------|-------|-------|-------|-------|-------|
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| R ² | 0.81 | 0.89 | 0.75 | 0.81 | 0.81 | 0.81 | 0.81 | 0.81 |
| Observations | 1 088 | 1 088 | 1 088 | 1 088 | 1 088 | 1 088 | 1 088 | 1 088 |

Notes: The Table reports results of the estimation with standard fixed effect estimator. Values in parentheses show Driscoll and Kraay (1998) standard errors. *, **, and *** denote statistical significance at 10%, 5% and 1% level. Column 1 and Columns 4-8 dependent variable is lagged credit gap that represents the deviation of credit-to-GDP ratio from the long-run trend estimated using recursive HP filter. Column 2 dependent variable is lagged credit gap that represents the deviation of credit-to-GDP ratio from the long-run trend estimated using cubic time polynomial. Column 3 dependent variable is yoy growth of credit. Liquidity is a dummy variable for presence/absence of the tight macroprudential regulation with respect to the bank liquidity. Regressions include country fixed effects, and all variables are constructed in accordance with the discussion provided in the main text. In Column 4, two-quarters policy lags and in Column 5, four-quarter policy lags are reported. Alternative definitions of control variables in covariates are used in Column 6 (GDP growth), Column 7 (real exchange rate) and Column 8 (central bank policy rates).

Figure 1. Indices of cumulative net tightening measures (pooled)



Notes: The chart shows the calculated cross-country sum of the cumulative number of net tightening macroprudential measures within each category: bank capital, credit activity, bank FX exposure, bank liquidity. All variables are constructed in accordance with the discussion provided in the main text.

Source: own calculations based on the IMaPP data.