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RESEARCH ARTICLE

Effectiveness of Macroprudential Policies on Credit Surge and Stop Episodes

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Abstract
When faced with capital flow and credit growth waves in recent years, policymakers have relied upon macroprudential regulation. This paper sheds light on a relatively less-analyzed policy issue: how macroprudential regulatory measures mitigate extreme credit growth episodes. We use a dynamic panel data approach to estimate the impact of MaPPs on credit growth volatility and the likelihood of credit growth boom and bust episodes. We find that MaPPs reduce credit growth volatility in both advanced economies (AEs) and emerging market economies (EMEs). In addition, MaPPs help to prevent credit surges in EMEs and stops in AEs. Our results show that there is a strong link between net capital flows and credit growth stop episodes. Net capital flow surges trigger a credit surge for EMEs. This suggests that policymakers should consider both MaPPs and capital flow management measures when designing policies to mitigate the risks associated with these phenomena.

Keywords Macroprudential policy · Capital flows · Credit surges · Credit stops

JEL Classification E58 · E61 · F34 · F41 · G18

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1 Introduction

This paper investigates a relatively less-analyzed policy issue: how macroprudential regulatory measures perform in the case of extreme credit growth episodes that are likely to follow capital flows. The literature, by and large, finds that MaPPs effectively reduce credit growth; however, it omits if MaPP is also a potent policy tool to impede extreme credit periods. It is a critical issue as policymakers like to have a compelling policy device to deal with credit surges and stops rather than only changes in credit volume. Likewise, the literature has shown that capital inflows (outflows) correspond to increased (decreased) credit growth, as it provides another means of funding. It further requires that the potent policy tool also works in the presence of capital flow waves or other extreme events.

Forbes and Warnock (2012, 2021) show that heightened capital flow volatility has frequently occurred in recent decades. Especially, EMEs have experienced such waves for decades, even intermittent surges and sudden stops. These waves led to parallel patterns in loan growth and caused credit surge and stop episodes, as shown by studies such as Arena et al. (2015). Various papers have further refined which type of flows, such as foreign direct investment (FDI), portfolio, debt so on, affect credit volumes (Calderon and Kubota 2012; Arena et al. 2015).

How to deal with credit events posed a policy challenge to policymakers of EMEs. Almost all of them first tried monetary policy: the central banks cut interest rates to revive their economies after a credit collapse and increased them to prevent financial and economic crises. However, in both cases, policymakers realized that monetary policy is (i) a broad instrument to apply and (ii) can be insufficient. In the wake of the Asian Financial Crisis, this was the conclusion. They then resorted to a new policy—macroprudential regulation of factors affecting loan supply and demand and loan-providing institutions' resilience to the extent that they pose a systemic risk to the economy (Aizenman 2019). It was somehow not a new policy, as the AEs implemented such measures when they faced the financial repression problem after the Second World War. Also, Germany substantially raised reserve requirement ratios in the late 1960s and early 1970s to prevent capital inflow waves. After the global financial crisis of 2008-9, AEs and EMEs were on the same page in dealing with extreme credit events. There is now a burgeoning empirical and theoretical literature on MaPP (Fendoglu 2017; Cerutti et al. 2017; Jeanne and Korinek 2020; Kuzman et al. 2022, among others).

We extend the literature by investigating whether MaPPs effectively mitigate extreme credit events considering the presence of capital flow waves. Unlike most studies, which mainly focus on net capital flows, we also allow for a breakdown of capital flows to FDI, portfolio, and other flows. Our investigation also covers the following issues. First, whether MaPPs are successful in both AEs and EMEs. Second, what are the linkages between credit growth and different types of capital flow episodes? More precisely, we consider credit growth as credit growth volatility and extreme events. Finally, what is the effectiveness of different types of MaPPs? The different economic and institutional settings in AEs and EMEs can affect the relationship between capital flows and credit episodes and the scope and success of MaPPs. This relationship would also differ based on the types of capital flows and the targeted MaPP instrument. Given that there are too many MaPP instruments—17 considered in this paper, compared to the monetary policy tools, identifying the most effective ones or subgroups would be desirable from a policymaking perspective.

Our empirical investigation starts with identifying surge and stop episodes for capital flows and credit growth, as in Forbes and Warnock (2012). We then quantify the MaPP stance by borrowing the measures from the IMF iMaPP database—a recent comprehensive index (Alam et al. 2019). Next, we investigate the effectiveness of MaPPs on credit growth during the capital surge and stop episodes using a fixed effects dynamic panel data estimation.

The model empirically examines how MaPPs affect credit growth volatility. A small number of cross-sectional units in the panel data set—34 countries— for a large number of dates—the sample period 2001:Q1–2018:Q4— gives rise to small sample biases in the commonly-used GMM-based estimation models. We, therefore, use an estimation technique that corrects such biases. Kiviet (1995) first developed such a model, known as the bias-corrected LSDV model. We utilize an extended version of this technique (Bruno 2005a, b), correcting several other biases and estimation issues, such as proliferation bias, heteroskedasticity, and autocorrelation problems. Next, we complement the dynamic panel estimation and investigate how the MaPPs affect the likelihood of credit episodes using a multinomial logit model following Bussiere and Fratzscher (2006).

In the empirical investigation stage of both models, we run estimations under several capital flow types (FDI flows, portfolio flows, other flows), two country groups (AEs and EMEs), and three subgroups of MaPPs (demand-based, supply-based, and other MaPPs). The results indicate that MaPP can be a potent policy tool in mitigating both the volatility and occurrences of extreme episodes in credit growth. However, the effectiveness of macroprudential regulation varies with AE and EME countries, capital flow types, and demand- and supply-based MaPP instruments. Also, our results point out that capital flow stops are associated with credit stops for both AEs and EMEs, while capital flow surges are linked with credit surges only for EMEs.

The remainder of this paper is organized as follows. Section 2 presents a review of the literature. Section 3 discusses the methodology and data employed for the empirical model. Section 4 discusses the results and policy implications, and Section 5 concludes.

2 Related Literature

Our paper draws from several strands of the literature. They are the effectiveness of macroprudential regulation, managing credit growth, impacts of and managing capital flows, and policy design under extreme events. A vast literature on capital flows analyses its determinants and impact on macroeconomic conditions, external balances, and systemic risk using aggregate and firm-level data. Two sub-literatures within these are related to our paper. The first is the literature on capital waves, with episodes of capital inflow and outflow surges and stops (Forbes and Warnock 2012).

Second, numerous papers are specifically interested in the effects of capital flows on credit variables such as loan growth and credit gap upon the widely accepted claim of credit conditions being the crucial determinant of systemic risk. Past studies have also linked credit booms with capital flows. Several empirical studies (Calderon and Kubota (2012); Furceri et al. (2012); Arena et al. (2015); Mendoza and Terrones (2008, 2012) among others) examine whether surges in private capital inflows lead to credit booms. In some of these papers (Furceri et al. 2012) and others (Verma and Sengupta 2020), researchers studied the link between different types of inflows on credit booms. Furceri et al. (2012) finds that "rising inflows of foreign capital—especially, driven by gross private other investment inflows are highly likely to lead to credit booms". Interestingly, the paper finds that surges of gross FDI inflows reduce the likelihood of credit booms. After the global financial crisis, credit bust episodes have also attracted the attention of researchers.

Numerous papers look into the dynamics of credit growth and their impacts on systemic risk. For example, Igan and Pinheiro (2011) explores the relationship between credit growth and bank soundness. Literature also documents a great deal of differentiation between credit dynamics in AEs and EMEs (Meng and Gonzalez 2017). Another distinction is on credit booms ending in crisis (bad boom) and no crisis (good boom) (Calderon and Kubota 2012; Dell'Ariccia et al. 2016; Castro and Martins 2020).

Finally, papers on macroprudential regulation have mushroomed to address the issue as countries are recently seeking new policy tools to deal with the constraints of policy trilemma, space, and repression issues (Bakker et al. 2012; Claessens et al. 2014; Cerutti et al. 2017; Cerutti et al. 2019; Fendoglu 2017).

Our paper differs from the literature described above in several ways. First, our paper is the first to study the effectiveness of MaPPs on the two symmetric credit growth episodes of surges and stops. Most papers do not analyze extreme credit events. One notable exception is Dell'Ariccia et al. (2016), where the focus is on the credit booms only. Second, Verma and Sengupta (2021), a close one to ours, does not study macroprudential policies and considers only EMEs to investigate how debt flows affect credit cycles. Third, we incorporate various capital inflow types with extreme events. Finally, the paper uses the most updated MaPP index and a comprehensive data set of quarterly global and country macroeconomic and financial variables.

3 Data and Empirical Estimation Approach

3.1 Data

Our work requires a comprehensive data set, including granular data on capital flows and MaPPs, credit volume, and primary domestic macroeconomic and global indicators. Such an extensive set at a quarterly frequency is available for 36 countries,

Table 1 Macroprudential Policy Instruments

#	Instrument	Type
1	Limits on Debt-Service-to-Income Ratio	Demand
2	Limits on Loan-To-Value Ratio	Demand
3	Capital Requirements	Supply
4	Conservation	Supply
5	Countercyclical Buffers	Supply
6	Leverage Limits	Supply
7	Systemically Important Financial Institution (SIFI)	Supply
8	Limits on Foreign Exchange Positions	Supply
9	Liquidity Requirements	Supply
10	Reserve Requirements	Supply
11	Limits on Credit Growth	Supply
12	Limits on Foreign Currency	Supply
13	Loan Loss Provisions	Supply
14	Loan Restrictions	Supply
15	Limits on the Loan-to-Deposit Ratio	Rest
16	Tax Measures	Rest
17	Other	Rest

The data source is the IMF-integrated Macroprudential Policy (iMaPP) database. Dataset is based on the Macroprudential Policy Survey of the IMF and additional information from the Bank for International Settlements and Financial Stability Board. See Alam et al. (2019) for details

with 22 AEs and 14 EMEs[1] The data set starts from 2001:Q1 and ends in 2018:Q4, reflecting a highly integrated capital markets era.

The macroprudential policy stance is the most imperative data item, and we utilize the most comprehensive iMaPP database constructed by Alam et al. (2019). This database combines information from various sources and provides MaPP indices for 17 instruments and their classification. Some instruments such as limits on credit growth are expected to be more effective than others. It is important to understand the effectiveness of the different MaPPs, however, some of these instruments do not show much variation. Because of this limitation, Alam et al. (2019) can not also analyze all instruments. They focus on loan-to-value ratios and debt service-to-income ratios as individual instruments. They form instrument groups to carry out their analysis. Similarly, we consider indices for the three instrument groups. Table 1 shows how the database classifies macroprudential regulatory measures as demand-, supply-based, and other MaPPs [See BIS (2020)].

[1] AEs are Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, United Kingdom, and the United States. EMEs are Argentina, Brazil, Chile, Colombia, Hungary, India, Indonesia, Korea, Mexico, Poland, Russia, South Africa, Thailand, and Turkey. Data is also available for Luxembourg, and Iceland, but these countries experienced excessive capital inflows during this period. Following the literature, we exclude these two countries from our sample of 36 countries.

The MaPP indices for each policy instrument take three values: +1 for policy tightening, −1 for loosening actions, and 0 when there is no change in the policy stance. It has the benefit of better capturing the adjustment dynamics compared to the customary 0-1 dummy structure, which only indicates the presence of policy tightening. We form a general MaPP index by summing the 17 sub-indices to measure the macroprudential policy stance. Accounting for lagged effects, we average the index over the previous four quarters as in Alam et al. (2019).

Our credit measure is the domestic currency-denominated loans to the private non-financial sector provided by the Bank for International Settlements (BIS). For capital flows, we use the detailed data set on FDI, portfolio, and others constructed by Forbes and Warnock (2021). Other flows are mostly bank related flows. VIX, G7 growth, and policy rates come from Fred Data - Federal Reserve Bank of St. Louis. We also use the BIS data for policy rates.

We determine surge and stop episodes for real credit growth and capital flows using the methodology of Forbes and Warnock (2012).[2] First, we divide the nominal credit value by the consumer price index (CPI) and then calculate year-on-year real credit growth for each country at each quarter in time. We calculate growth rates for capital flows as a four-quarter moving sum in US dollars. We compute the annual growth rates' rolling means and standard deviations over the previous five years.

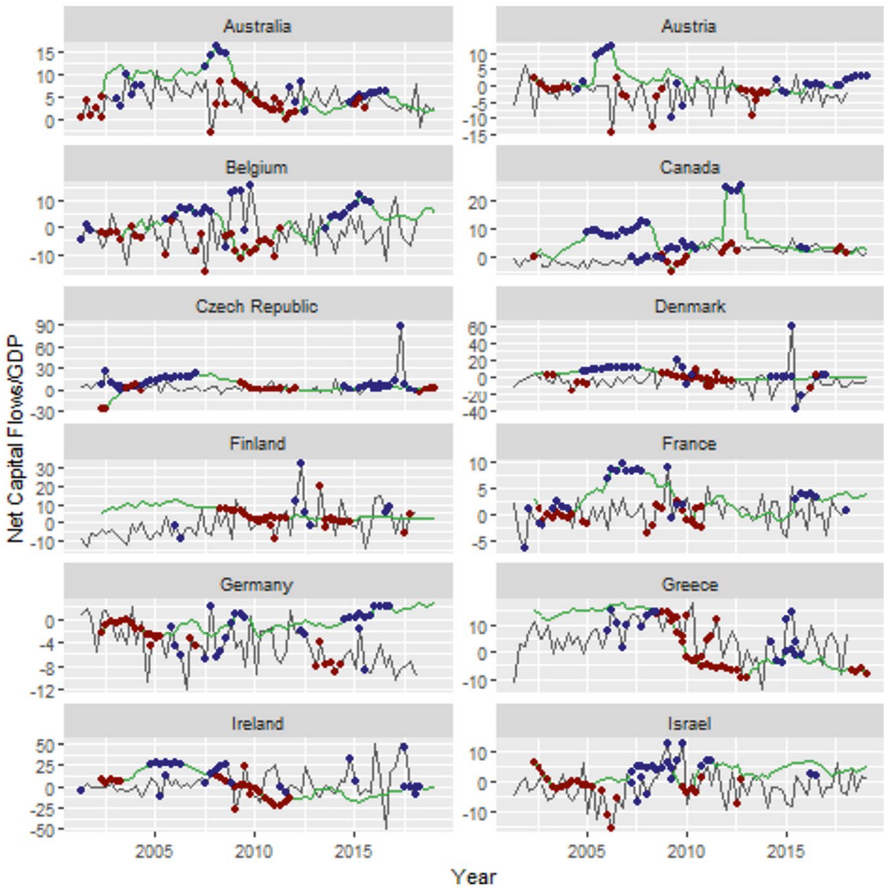
Following Forbes and Warnock (2012), we define a surge episode (for both credit growth and capital flows) as a period in which growth rates are more than one standard deviation above its rolling mean. Also, there must be at least one quarter in which the growth rate is at least 1.5 standard deviations above the mean, and the episode has to last longer than one quarter. A stop episode is symmetrical to the surge with negative growth rates. We also define the episodes using different threshold levels, specifically 1.7 and 2 standard deviations above the mean as robustness checks.

Table 7 in the appendix reports the start and end dates of each country's credit growth surge and stop episodes. Likewise, Table 8 provides the same information for surge and stop episodes in net capital flows. Figure 1 provides the visual representation of credit and capital flow episodes.

3.2 Empirical Estimation Approach

We empirically analyze our panel data set using two estimation approaches: (i) a fixed effects regression model and (ii) a multinomial logit regression model. The first enables us to investigate the interlinkage between credit growth volatility

[2] There are different approaches for credit boom (surge) identification and hence no consensus. See (Arena et al. 2015; Ghosh et al. 2014; Mendoza and Terrones 2012; Gourinchas et al. 2001; Beck et al. 2013; Gourinchas et al. 2001; Tornell and Westermann 2002 among others) for alternative specifications. The widely accepted approach compares the country's real credit per capita or the credit to GDP ratio to a long-term trend. The studies also disagree on the specifics of the calculation methodology. Amri et al. (2016) and Crystallin et al. (2015) analyze the implications of different identification approaches. Note that, we use "credit boom/bust" and "credit surge/stop" terms interchangeably in this study.

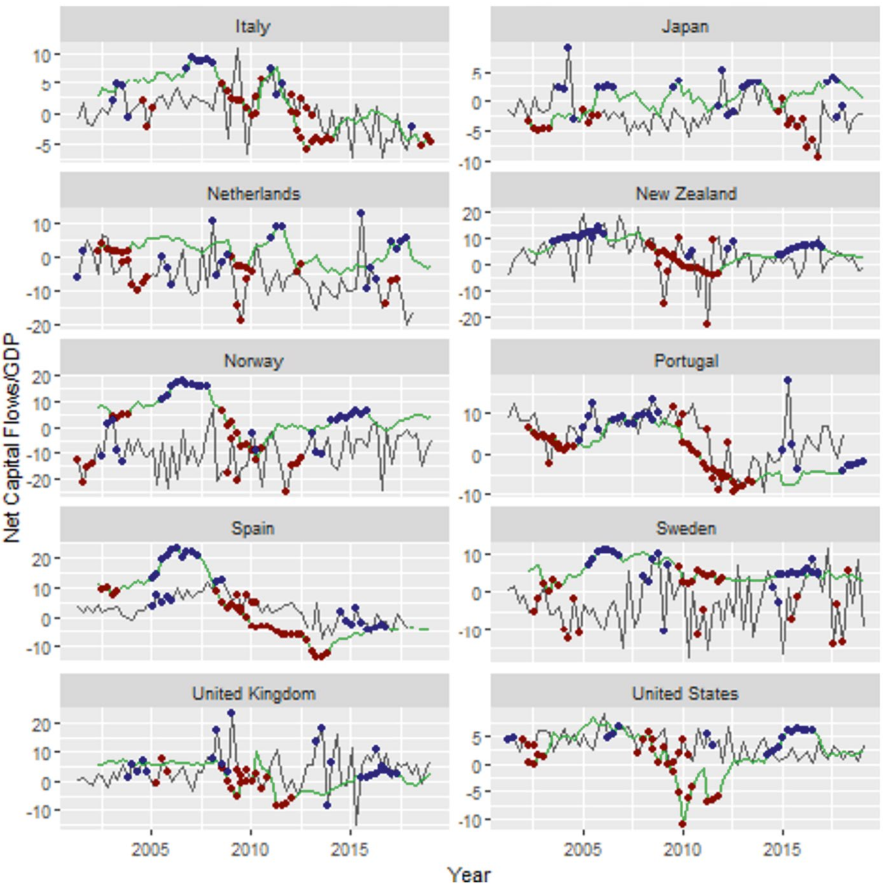


Panel A: AEs

Fig. 1 Credit and Capital Flow Surge and Stop Episodes

and MaPPs. The second explores the relationship between credit surge/stop episodes and MaPPs.

Our fixed effects panel estimation method departs from the widely used one based on an instrumental variable (IV) and generalized method of moments (GMM) estimators (such as Arellano and Bond (1991); Blundell and Bond (1998)) and is a bias-corrected LSDV estimator. The small number of cross-sectional units in our panel data set gives rise to small sample biases. More precisely, the IV and GMM-based estimators become severely biased when the panel data includes few cross-sections (*N*) and many periods (*T*). Kiviet (1995) developed a bias-corrective procedure on the LSDV method. Bruno (2005a, b) further augmented the Kiviet model to capture unbalanced dynamic panel data sets such as proliferation bias—the number of instruments become too high due to the large *T*.



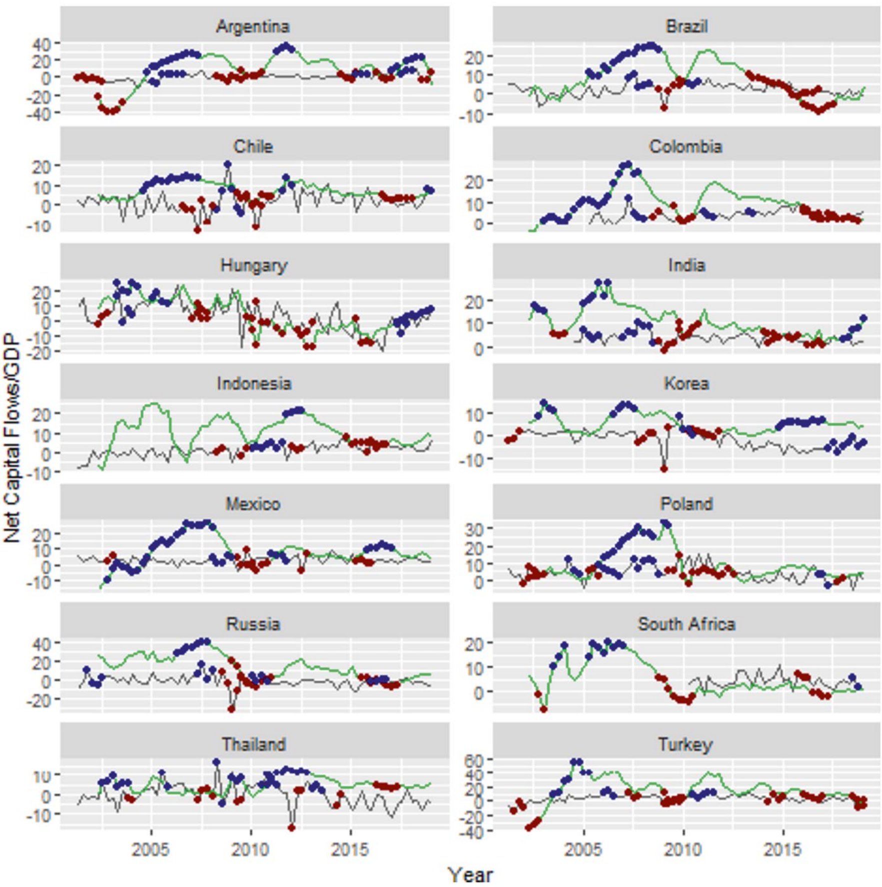
Panel A: AEs (Continued)

Fig. 1 (continued)

To sum up, the LSDV estimation improves the dynamic panel GMM estimators by addressing the small-sample and proliferation bias problems and providing efficient and consistent estimators for the panel data with few cross-sections and long time-periods.[3]

The fixed-effects panel estimation equation is given by

[3] The LSDV also addresses the issue of heteroskedasticity and autocorrelation in the dataset. Furthermore, the method automatically drops explanatory variables due to collinearity among variables. We use the STATA procedure "xtlsdvc" to estimate the model as provided by Bruno (2005a). We choose the Anderson-Hsiao estimator as the initial estimator to avoid invalid and too many instruments. Further, we use bootstrapped standard errors with 100 replications following Bruno (2005b).



Panel B: EMEs

Note: Grey lines show the ratio of capital flows to GDP scaled by multiplying with 100,000. Green lines show credit growth rates as percentage numbers. Credit growth rates are shown in green and as percentage numbers. Dark red points represent credit or capital flow stop episodes, and dark blue points represent surge episodes.

Fig. 1 (continued)

$$\sigma(CreditGrowth)_{i,t} = \alpha_0 + \alpha_1 \sigma(CreditGrowth)_{i,t-1} + \alpha_2 MaPP_{i,t-1} + \beta X_{i,t-1} + \mu_i + \epsilon_{i,t} \tag{1}$$

where $\sigma(CreditGrowth)_{i,t}$ is the four-quarter rolling standard deviation of the quarterly growth rate of real credit at time t for country i. $MaPP$ denotes the macroprudential policy stance, and X represents other key explanatory variables that comprise domestic variables, namely monetary policy rates and GDP growth rates, and global variables, such as the change in VIX and average GDP growth rates of G7 countries. We also include the four-quarter averaged net flows to GDP ratio. The term μ_i captures country-fixed effects while ϵ is the time and country-specific error term.

After investigating the impact of MaPP on credit growth volatility using the above-described LSDV, we apply logistic regression analysis to measure the effects of MaPP on credit growth surge and stop episodes. More precisely, to assess the role of MAPP, capital flow episodes, and global and domestic variables on the conditional probability of having a surge, stop, or tranquil episode of credit growth, we estimate the following benchmark multinomial logit model:

$$\begin{aligned} Credit(surge/stop/tranquil)_{i,t} = \beta_1(CF^{stop})_{i,t-1} + \beta_2(CF^{surge})_{i,t-1} \\ + \beta_3 MaPP_{i,t-1} + \beta_4 \mathrm{X}_{i,t-1} + \mu_i + \epsilon_{i,t}, \end{aligned} \tag{2}$$

where CF^{surge} (CF^{stop}) is a dummy variable, representing if the country is in a capital surge (stop) episode (based on net flows), and MaPP captures the macroprudential policy stance. X denotes the control variables, which include the global indicators—the G7 GDP growth rate and the change in the VIX— and the one period lagged domestic variables (to tackle with endogeneity) —policy rates and GDP growth rates. μ_i again captures country-fixed effects, and ϵ is the country and time-specific error term. The estimation approach in Eq. (2) is a commonly used one in the literature (see, for example, Forbes and Warnock (2021); Forbes (2021)).[4] Verma and Sengupta (2021) also estimate a version of Eq. (2) using only debt flows. This specification allows us to capture how countries' use of MaPPs (loosening or tightening) has affected their probability of experiencing a surge or stop in credit growth. In other words, were countries that have tightened (loosened) MaPPs less (more) exposed to the risk of credit growth boom or stop episodes?

4 Results

4.1 Results for Credit Growth Volatility and MaPP

We carried out the regressions of the model specified in Eq. (1) over the whole sample and separately over the AEs and EMEs. Table 2 shows that MaPPs are effective policy instruments in reducing credit growth volatility both in AEs and EMEs. Consistent with the findings of the earlier work, MaPPs have higher coefficient values in EMEs than the AEs. We also re-estimate our model with alternative volatility measures where the horizon is longer. Specifically, we use rolling standard deviations eight and twenty quarters. Results are reported in Appendix Table 9. We observe that coefficients are negative but only significant for AEs.

It is interesting to note that the impact of other variables on the volatility of credit growth is country-group specific, i.e., they are effective either in AEs or EMEs but not in both countries. G7 and country-specific GDP growth rates reduce credit growth volatility, while policy rates and changes in the VIX increase it. The former might indicate that benign economic conditions imply good news for credit growth volatility, while the latter suggests that policy rate hikes and VIX increases mean

[4] More precisely, they use a "complementary logarithmic (or cloglog) framework".

Table 2 MaPP Stance and Credit Growth Volatility (bias-corrected LSDV model)

Dependent variable is credit growth volatility			
	Full Sample	AE	EME
Lagged Credit Growth Volatility	0.722***	0.727***	0.714***
	(51.88)	(37.13)	(29.34)
MaPP	−0.075**	−0.087*	−0.115**
	(−2.10)	(−1.95)	(−2.02)
GDP Growth	−0.035***	−0.019	−0.053**
	(−2.68)	(−1.40)	(−1.96)
Policy Rate	0.035***	0.007	0.039***
	(7.72)	(0.66)	(5.42)
VIX Change	0.007***	0.004	0.012***
	(2.72)	(1.62)	(2.36)
G7 GDP Growth	−0.020**	−0.022**	−0.017
	(−2.25)	(−2.28)	(−0.90)
$\frac{\text{Net Flows}}{\text{GDP}}$	3.279	0.868	7.601
	(0.81)	(0.25)	(0.83)
# of Observations	2285	1437	848
# of Countries	36	22	14

This table presents the estimation results from Eq. (1). The dependent variable is credit growth volatility. t statistics in parentheses

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$

adverse market conditions for credit growth volatility. Net capital flows to GDP ratio is not statistically significant.

Since MaPP measures are effective on credit growth volatility, we conduct a follow-up investigation to determine which MaPP measures are effective. More precisely, we consider the subcategories of MaPPs: demand-based MaPP, supply-based, and rest.

4.2 Results for Credit Growth Volatility and Disaggregated MaPP Measures

The effect of MaPPs on credit growth volatility may vary across its subgroups. To identify which MaPP subgroup is effective in mitigating credit growth volatility, we estimate the model specified in Eq. (1) using disaggregated MaPP measures. There is not much variation in many individual tools. Therefore, we consider aggregate indices for instrument groups following Alam et al. (2019).[5] We now form three

[5] Despite the lack of variation, we report the results with individual instruments for credit growth volatility in the Appendix Table 10. Considering the results with full sample, volatility regressions reveal that the use of capital requirements, reserve requirements, and limits on loan-to-deposit ratio measures significantly reduce credit growth volatility.

Table 3 Credit Growth Volatility and Disaggregated MaPPs (bias-corrected LSDV model)

Dependent variable is credit growth volatility			
	Full Sample	AE	EME
Panel A: Aggregate Policy Index			
MaPP	−0.075**	−0.087*	−0.115**
	(−2.10)	(−1.95)	(−2.02)
Panel B: Disaggregated Policy Indices			
$MaPP^{demand}$	0.103	−0.016	0.105
	(1.04)	(−0.10)	(0.57)
$MaPP^{supply}$	−0.106**	−0.111*	−0.140**
	(−2.43)	(1.87)	(−2.09)
$MaPP^{rest}$	−0.154	−0.124	−0.334
	(−0.89)	(−0.80)	(−0.96)
# of Observations	2285	1437	848
# of Countries	36	22	14

This table presents the estimation results from Eq. (1). The dependent variable is credit growth volatility. t statistics in parentheses

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$

subindices of the MaPP index based on the type of instruments they target: demand-side, supply-side, and the rest (see Table 1).

Table 3 reports the new results in Panel B and reprints the summary results from Table 2 in Panel A. Panel B highlights that supply-based MaPP measures are potent instruments in reducing credit growth volatility. However, demand-based measures and the rest are ineffective. This result is valid for the whole sample and the AEs and EMEs.

4.3 Results for Credit Growth Episodes and MAPP

After having established the effectiveness of MaPP on credit growth volatility, we carry out our investigation further. Using the logistic regression methodology, we test the effectiveness of MaPP on credit surge, stop, and tranquil episodes. In this specification, we consider extreme episodes of capital flows to see how they are related to extreme credit growth events. Table 4 reports the relative risk ratios (RRRs) for the multinomial logit model specified in Eq. (2). RRR is greater (less) than one if the risk of being in the surge/stop episode, compared to that in a tranquil state, increases as the variable increases (decreases). Estimations cover the whole sample and separately AEs and EMEs. The takeaway is that MaPP can be an effective policy tool in managing credit growth episodes. In AEs, MaPPs reduce the probability of stop episodes, while in EMEs, they successfully mitigate surge episodes.

The results also reveal a profound relationship between credit and capital flow episodes. A stop in net capital flows increases the probability of credit growth stops irrespective of the sample group. However, a surge increases the probability of

Table 4 Credit Surge/Stop Episodes, Net Capital Flows and MaPPs

	Credit Stop			Credit Surge		
	Full Sample	AE	EME	Full Sample	AE	EME
MaPP	0.467***	0.310***	0.807	0.760**	1.075	0.571***
	(−4.74)	(−3.59)	(−1.07)	(−2.18)	(0.37)	(−3.09)
Policy Rate	1.065***	1.363***	1.032**	1.012	1.077	1.016
	(5.40)	(6.60)	(2.12)	(1.01)	(1.63)	(1.09)
GDP Growth	0.761***	0.697***	0.786***	1.078***	1.100***	1.050
	(−10.69)	(−8.03)	(−6.51)	(3.46)	(2.94)	(1.41)
VIX Change	1.004	1.006	0.990	1.016	1.014	1.016
	(0.43)	(0.54)	(−0.76)	(1.30)	(0.89)	(0.85)
G7 GDP Growth	0.876***	0.867***	0.935	1.304***	1.203**	1.404***
	(−3.50)	(−2.56)	(−1.10)	(4.03)	(2.09)	(3.32)
Net Flows Surge	1.047	0.986	0.933	1.043	0.768	1.653**
	(0.28)	(−0.07)	(−0.23)	(0.29)	(−1.31)	(2.32)
Net Flows Stop	1.760***	2.040***	1.522*	0.866	0.966	0.803
	(3.68)	(3.51)	(1.68)	(−0.83)	(−0.16)	(−0.72)
Observations	2370	1466	904			
Pseudo R-squared	0.116	0.150	0.105			

This table presents the estimation results from Eq. (2). The dependent variable is a dummy variable indicating if there is a credit growth episode (surge, stop, or normal). Exponentiated coefficients (relative risk ratios - RRR); t statistics in parentheses

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$

credit growth surges only in EMEs. These findings point to the different dynamics in AEs and EMEs to capital flows and are consistent with earlier papers on credit growth that did not focus on extreme events. For example, Carvalho (2021) finds no correlation between capital flows and credit growth in AEs, while several researchers (Mendoza and Terrones 2012; Lane and McQuade 2014, among many), including the celebrated work of Calvo (1998), have found high correlations for EMEs. Also, our results are consistent with the findings of Verma and Sengupta (2021), who focus on stop and surge episodes in external debt financing and credit growth for a subset of our EMEs sample.

Domestic and global factors also influence the probability of credit surge and stop episodes. GDP growth rate is the most significant variable affecting the occurrence of both surge and stop episodes. The results show that a higher (lower) GDP growth rate increases the probability of credit surges (stops). This finding is in line with the expectation and the literature. Higher GDP, a sign of a good-performing economy, means higher economic activity and increased demand for credit, which would increase the likelihood of a credit boom. What is striking, however, is that the relationship does not hold for EMEs and higher domestic GDP growth is not a significant factor leading to credit surges in EMEs. Instead, in EMEs, surges in credit are driven by G7 growth. Higher (lower) average growth rate of G7 countries is associated with higher (lower) probability of credit surges both in AEs and EMEs, while higher (lower) average growth rate of G7 is associated with lower (higher) probability of credit stop episodes in AEs but is not significant for EMEs.

The domestic policy rate is also not significant for credit surges both in AEs and EMEs. It is significant, however, only for credit stops. Higher policy rates increase the likelihood of credit stops both in AEs and EMEs, as expected. We do not find a significant relationship between global market uncertainty, measured via VIX, and credit growth episodes. These findings indicate that domestic factors are more significant drivers of stop episodes. For EMEs, surges are driven more by global growth and capital inflows.

To test the robustness of the results for the definition of the surge and stops for real credit growth and net capital flows, we follow two different approaches. First, we use different threshold levels of stop/surge events in the Forbes and Warnock (2012) methodology. Secondly, we define the stop and surge events following the methodology of Ghosh et al. (2014). This methodology classifies an observation as a surge if it lies in the top 30th percentile of the country's own distribution of net capital flows (as a share of GDP) and also in the top 30th percentile of the entire sample's distribution. Stops are identified symmetrically by using the bottom 30th percentile using the same definition. Results are reported in Appendix Table 12. Results are robust to the alternative definitions of stop/surge episodes.

4.4 Results for Credit Growth Episodes and Disaggregated Capital Flows

Next, we identify surge and stop episodes for different types of capital flows (direct, portfolio, and other flows) and re-estimate Eq. (2) separately using each specific type of capital flow episode.[6] The results in Table 5 reveal that capital flow types matter in their impacts on credit stop-surge episodes and across country groups.

Stops in direct flows (Panel B) are likely to generate credit stops, while surges in direct flows reduce their probability in EMEs. We observe a similar pattern for other flows (Panel D) in AEs: stops in other flows increase while their surges reduce the probability of credit stops. Surges in portfolio flows (Panel C) increase the probability of credit stops in EMEs, while portfolio flow stops (Panel C) do not affect credit stops in either group of economies.

When we look at the probability of credit surges, the results reveal that credit surges in EMEs are mainly driven by surges in other flows. This is in line with Calderon and Kubota (2012), who show that surges in other inflows increase the likelihood of domestic credit booms. However, while they show that an increase in direct inflows mitigates the probability of credit booms, we do not find a significant effect of direct inflow surges (or stops) on credit surges (panel B).[7] Portfolio flow stops and surges (Panels C) do not affect credit surge episodes either.

[6] Panel A reproduces the results in Table 4 for comparison.

[7] Note that they do not distinguish between the type of economies and do not control for MaPP measures.

Table 5 Credit Surge/Stop Episodes and Components of Capital Flows

	Credit Stop			Credit Surge		
	Full Sample	AE	EME	Full Sample	AE	EME
Panel A: Net Flows						
MaPP	0.467***	0.310***	0.807	0.760**	1.075	0.571***
	(−4.74)	(−3.59)	(−1.07)	(−2.18)	(0.37)	(−3.09)
Surge	1.047	0.986	0.933	1.043	0.768	1.653**
	(0.28)	(−0.07)	(−0.23)	(0.29)	(−1.31)	(2.32)
Stop	1.760***	2.040***	1.522*	0.866	0.966	0.803
	(3.68)	(3.51)	(1.68)	(−0.83)	(−0.16)	(−0.72)
Panel B: Direct Flows						
MaPP	0.464***	0.315***	0.824	0.764**	1.100	0.598***
	(−4.79)	(−3.60)	(−0.96)	(−2.13)	(0.49)	(−2.83)
Surge	0.696**	0.766	0.510**	0.813	0.919	0.687
	(−2.04)	(−1.16)	(−2.13)	(−1.32)	(−0.40)	(−1.59)
Stop	1.241	0.768	2.130***	1.221	1.114	1.380
	(1.36)	(−1.16)	(3.18)	(1.37)	(0.58)	(1.32)
Panel C: Portfolio Flows						
MaPP	0.470***	0.305***	0.791	0.758**	1.091	0.601***
	(−4.73)	(−3.70)	(−1.18)	(−2.20)	(0.44)	(−2.82)
Surge	1.552***	1.195	1.789**	0.772	0.772	0.793
	(2.82)	(0.86)	(2.37)	(−1.64)	(−1.21)	(−0.96)
Stop	1.117	1.153	0.950	0.914	1.005	0.837
	(0.69)	(0.67)	(−0.20)	(−0.58)	(0.02)	(−0.75)
Panel D: Other Flows						
MaPP	0.471***	0.304***	0.805	0.765**	1.113	0.831***
	(−4.69)	(−3.64)	(−1.10)	(−2.13)	(0.55)	(−2.97)
Surge	0.795	0.640*	0.912	1.172	0.956	1.504*
	(−1.29)	(−1.91)	(−0.32)	(1.08)	(−0.22)	(1.87)
Stop	1.804***	2.161***	1.382	1.179	1.397*	0.956
	(3.88)	(3.88)	(1.30)	(1.04)	(1.65)	(−0.17)

This table presents the estimation results from Eq. (2). The dependent variable is a dummy variable indicating if there is a credit growth episode (surge, stop, or normal). Exponentiated coefficients (relative risk ratios - RRR) on MaPP and capital flow surge/stop dummies are reported. Results on other variables are not reported to conserve the space, t statistics in parentheses

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$

Overall, the results in Table 5 indicate that capital flows, in general, significantly affect credit growth stops more than surges. However, surges in capital flows increase the likelihood of credit surges for EMEs, and surges in other flows drive the relationship.

Table 6 Credit Surge/Stop Episodes and Disaggregated MaPPs

	Credit Stop			Credit Surge		
	Full Sample	AE	EME	Full Sample	AE	EME
Panel A: Aggregate Policy Index						
MaPP	0.467***	0.310***	0.807	0.760**	1.075	0.571***
	(−4.74)	(−3.59)	(−1.07)	(−2.18)	(0.37)	(−3.09)
Panel B: Dis-aggregated Policy Indices						
$MaPP^{demand}$	1.133	0.528	1.618	0.318***	0.163***	0.394
	(0.26)	(−0.75)	(0.86)	(−2.67)	(−2.56)	(−1.61)
$MaPP^{supply}$	0.434***	0.192***	0.872	0.933	1.715**	0.617**
	(−4.48)	(−3.84)	(−0.61)	(−0.49)	(2.36)	(−2.37)
$MaPP^{rest}$	0.165**	1.781	0.013***	0.242**	0.238*	0.294
	(−2.34)	(0.58)	(−3.15)	(−2.20)	(−1.74)	(−1.16)

This table presents the estimation results from Eq. (2). The dependent variable is a dummy variable indicating if there is a credit growth episode (surge, stop, or normal). Exponentiated coefficients (relative risk ratios - RRR); t statistics in parentheses

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$

4.5 Results for Credit Growth Episodes and Disaggregated MaPPs

The results with the aggregate MaPP index show that MaPPs reduce the probability of credit stops in AEs, while in EMEs, they are effective at lowering the probability of credit surges. This finding warrants further investigation into the effectiveness of disaggregated MaPP measures between country groups. We consider the dis-aggregation methods following Alam et al. (2019). First, we classify MaPPs as (i) demand-based (limits on loan to value and debt service to income ratios), (ii) supply-based (such as limits on credit growth and loan loss provisions),[8] and (iii) the rest (taxes, levies, loan-to-deposit ratio, and others), which affects both supply and demand.

Table 6 shows that supply-based MaPPs reduce the probability of credit surges, while the rest of the MaPPs effectively lower the probability of credit stops for EMEs (Panel B). Considering AEs, demand-based MaPPs and the rest of MaPPs reduce the probability of credit surges.[9] Supply-based measures reduce the probability of credit stops and increase the probability of credit surges.[10] This finding may reflect

[8] See Table 1 for the full list of supply based measures. Results with individual instruments are reported in Appendix Table 11. MaPP measures under the categories of counter-cyclical buffers, systemically important financial institutions, liquidity requirements, limits on credit growth, loan-loss provisions, and tax measures significantly reduce the probability of credit stop episodes for the full sample. Limits on loan-to-value ratios, counter-cyclical buffers, limits on foreign exchange positions, liquidity requirements, limits on credit growth, limits on foreign currency, loan-loss provisions, and tax measures are potent instruments to reduce credit surge episodes.

[9] Panel A reproduces the results reported in Table 4 for comparison.

[10] Note that these findings are different than those reported in Table 3 where only supply-based measures were significant. The surge/stop specification gives a more distinct measure of extreme periods in credit growth. Hence, the nature of the credit measures matters for the assessment of the effectiveness of MaPP indices.

the two main objectives of macroprudential regulation: (i) to manage credit supply and demand and (ii) to “increase the resilience of the financial system to aggregate shocks by building and releasing buffers that help maintain the ability of the financial system to function effectively, even under adverse conditions" (Financial Stability Board et al. 2016).

5 Conclusion

We contribute to the burgeoning empirical literature on the effectiveness of macroprudential policies (MaPPs) on credit by providing a dynamic panel data investigation of their effect on both the volatility and occurrence of extreme episodes of credit growth. We employ a bias-corrected least squares dummy variable (LSDV) model and a multinomial logit estimation approach.

The results of the LSDV model provide evidence that MaPPs mitigate credit growth volatility in both advanced economies (AEs) and emerging market economies (EMEs). The multinomial logit model results show that MaPPs affect credit growth episodes, but their effectiveness varies between country groups and surge-stop episodes. Our results suggest that MaPPs can be an effective tool for preventing credit booms and busts. They can be particularly effective in AEs to mitigate the credit stop episodes. In EMEs, MaPPs reduce the probability of credit surges.

Our results also show the occurrence of credit growth episodes vary depending on the type of capital flow episode: (i) Net capital flow stops increase the likelihood of credit growth stops, while surges increase that of credit growth surges only in EMEs; (ii) Considering components of capital flows, direct flow stops in EMEs, and other flow stops in AEs increase the likelihood of credit growth stops. At the same time, their surges decrease that of credit growth stops. This finding implies that direct flows are more critical for EMEs and other flows for AEs. In contrast, portfolio surges increase the probability of credit stops in EMEs, reducing the probability of credit surges in AEs; and (iii) The findings with disaggregated flows shed light to the results with the net capital flows. Other flows drive the link between net capital flow stops and credit stops for AEs, as well as the relationship between capital flow and credit surges for EMEs. These results are consistent with the findings of Furceri et al. (2012).

Our results have important policy implications. The findings on extreme episodes provide evidence of the channel through which MaPPs reduce credit growth volatility, indicating that they increase the resilience of financial institutions. Furthermore, the use of macroprudential instruments is found to be effective in mitigating extreme episodes of credit growth extending the literature where the general focus is on credit growth. Our exercises on the subgroups of MAPPs help to understand which tools are most effective against an expected extreme event. This can guide the targeted use of MAPPs. Finally, our work sheds light on the link between capital flow episodes and credit surge/stop events.

Future work could use a more granular capital flow episodes data, including capital flights and retrenchments, to explore if the results obtained in this paper are driven by domestic or foreign investors. A firm-level data set with episodes on capital flows and credit variables would shed light on MaPPs' firm-level effects. Academic research could also explore if changes in MaPPs could affect capital flow episodes and their sensitivity to global developments. Furthermore, MaPPs can potentially weaken the link between capital flow and credit episodes. Examining this issue and exploring the effects of different MaPP instruments can be very useful in designing policies.

Appendix: Episodes of Capital Flows and Credit Growth

Table 7 Credit Surge/Stop Episodes

	Credit Surge		Credit Stop	
	Start	End	Start	End
Argentina	2004Q3	2007Q1	2001Q1	2003Q2
	2011Q1	2011Q4	2009Q2	2010Q2
	2017Q3	2018Q2	2014Q2	2015Q1
			2016Q1	2016Q4
Australia	2007Q2	2008Q2	2001Q1	2002Q1
	2014Q3	2016Q2	2008Q4	2011Q4
Austria	2005Q2	2006Q1	2001Q3	2003Q4
	2015Q4	2016Q3	2012Q3	2013Q4
	2017Q2	2018Q4		
Belgium	2005Q2	2007Q3	2001Q1	2003Q1
	2013Q2	2015Q3	2008Q2	2009Q4
Brazil	2005Q1	2008Q3	2009Q3	2009Q4
			2013Q1	2017Q2
Canada	2004Q4	2007Q4	2001Q1	2002Q1
	2011Q4	2012Q3	2008Q3	2010Q2
Chile	2004Q2	2007Q1	2009Q1	2010Q4
			2016Q2	2017Q4
Colombia	2002Q4	2007Q3	2009Q2	2010Q2
			2015Q4	2018Q3
Czech Republic	2003Q1	2006Q4	2001Q3	2002Q2
	2015Q1	2016Q3	2009Q1	2011Q1
Denmark	2004Q3	2007Q2	2002Q4	2003Q1
	2014Q1	2015Q1	2008Q3	2012Q1
	2016Q2	2016Q4		
Finland	2001Q1	2001Q4	2008Q1	2011Q2
			2013Q2	2014Q3
France	2005Q4	2007Q3	2002Q2	2004Q1
	2015Q2	2016Q2	2009Q2	2010Q3
Germany	2008Q3	2009Q2	2001Q1	2005Q1
	2014Q2	2016Q3		
Greece	2001Q1	2001Q4	2008Q2	2012Q4
	2014Q4	2015Q2	2018Q1	2018Q4

Table 7 (continued)

	Credit Surge		Credit Stop	
	Start	End	Start	End
Hungary	2003Q1	2004Q1	2007Q1	2007Q3
	2017Q1	2018Q4	2009Q3	2010Q3
			2011Q1	2011Q2
			2012Q1	2012Q4
India	2002Q2	2002Q4	2003Q2	2003Q4
	2004Q4	2006Q1	2009Q3	2010Q3
	2018Q2	2018Q4	2013Q4	2014Q3
			2015Q1	2015Q3
Indonesia	2011Q3	2012Q2	2014Q3	2016Q3
Ireland	2004Q3	2006Q1	2001Q1	2003Q1
	2017Q2	2018Q1	2007Q4	2011Q3
Israel	2007Q1	2009Q1	2001Q4	2005Q1
	2010Q3	2011Q1	2009Q3	2010Q1
Italy	2006Q3	2007Q4	2008Q2	2010Q1
			2011Q4	2013Q4
			2018Q2	2018Q4
Japan	2005Q3	2006Q2	2002Q1	2003Q1
	2009Q2	2009Q3		
	2012Q4	2013Q3		
	2017Q1	2017Q3		
Korea	2002Q3	2003Q2	2009Q4	2011Q3
	2006Q2	2007Q2		
	2014Q3	2016Q4		
Mexico	2002Q3	2007Q4	2009Q1	2010Q3
	2015Q3	2016Q4		
Netherlands	2010Q4	2011Q2	2001Q3	2003Q3
	2016Q4	2017Q3	2008Q4	2009Q3
			2012Q1	2012Q2
New Zealand	2003Q2	2005Q4	2008Q1	2011Q3
	2014Q3	2016Q4		
Norway	2005Q2	2007Q3	2002Q4	2003Q3
	2013Q4	2015Q3	2008Q2	2010Q2
Poland	2005Q3	2008Q2	2001Q1	2002Q4
	2008Q4	2009Q1	2009Q4	2011Q2
Portugal	2006Q2	2008Q2	2001Q2	2004Q2
	2017Q4	2018Q4	2009Q4	2013Q2
Russia	2006Q1	2007Q3	2008Q4	2010Q4
			2015Q2	2017Q1
South Africa	2003Q2	2003Q4	2001Q1	2001Q2
	2005Q1	2006Q4	2002Q3	2002Q4
			2008Q3	2010Q2
			2016Q2	2017Q1

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Table 7 (continued)

	Credit Surge		Credit Stop	
	Start	End	Start	End
Spain	2004Q4	2007Q1	2002Q2	2003Q1
	2015Q3	2016Q3	2008Q1	2013Q3
Sweden	2005Q1	2006Q3	2002Q4	2003Q3
	2014Q3	2015Q4	2009Q3	2011Q4
	2016Q2	2016Q3		
Thailand	2002Q2	2003Q3	2016Q1	2017Q1
	2008Q4	2009Q2		
	2010Q3	2012Q3		
Turkey	2003Q2	2005Q1	2001Q2	2002Q3
			2008Q4	2009Q4
			2015Q4	2016Q4
United Kingdom	2015Q2	2017Q1	2008Q2	2009Q3
			2011Q1	2011Q4
United States	2014Q1	2016Q2	2001Q2	2002Q4
			2008Q2	2010Q2
			2011Q1	2011Q3

The episodes are calculated based on a 20-quarter rolling average. Due to data limitations, our sample starts from 2001Q1. New Zealand has a stop episode, and Denmark, France, Italy, United Kingdom have credit surge episodes which end by 2001Q1 which are not included in the list

Table 8 Net Capital Flows Surge/Stop Episodes

	Net Flow Surge		Net Flow Stop	
	Start	End	Start	End
Argentina	2004Q4	2006Q2	2001Q1	2002Q2
	2015Q1	2015Q3	2008Q1	2009Q2
	2016Q4	2017Q4	2018Q2	2018Q4
Australia	2002Q4	2004Q1	2001Q1	2002Q1
	2011Q3	2012Q2	2007Q3	2008Q2
			2010Q4	2011Q1
			2014Q4	2015Q2
Austria	2004Q2	2004Q3	2006Q1	2006Q4
	2009Q1	2009Q3	2008Q1	2008Q3
	2014Q2	2014Q4	2013Q1	2013Q4
Belgium	2001Q1	2001Q3	2003Q3	2004Q1
	2008Q2	2009Q4	2005Q2	2005Q3
	2018Q3	2018Q4	2006Q4	2007Q2
			2010Q1	2011Q1
Brazil	2007Q1	2008Q1	2008Q3	2009Q3
	2010Q1	2010Q3	2015Q4	2016Q3

Table 8 (continued)

	Net Flow Surge		Net Flow Stop	
	Start	End	Start	End
Canada	2007Q1	2007Q4	2011Q3	2012Q2
	2008Q2	2010Q2	2017Q2	2017Q4
	2015Q3	2015Q4		
Chile	2008Q1	2009Q2	2006Q2	2007Q4
	2011Q2	2011Q4	2009Q3	2010Q2
	2018Q3	2018Q4		
Colombia	2001Q1	2001Q4	2008Q2	2008Q3
	2010Q4	2011Q2	2015Q4	2017Q2
	2013Q1	2013Q2		
Czech Republic	2002Q1	2003Q1	2003Q2	2004Q1
	2014Q2	2014Q3	2011Q3	2011Q4
	2015Q4	2016Q2	2018Q1	2018Q4
	2016Q4	2017Q4		
Denmark	2009Q2	2010Q1	2004Q1	2004Q4
	2015Q1	2015Q3	2010Q2	2011Q2
			2016Q1	2016Q2
Finland	2005Q4	2006Q1	2010Q1	2010Q4
	2011Q4	2012Q3	2013Q1	2013Q3
	2016Q2	2016Q3	2017Q2	2017Q3
France	2001Q3	2001Q4	2004Q3	2004Q4
	2002Q2	2002Q3	2007Q4	2008Q3
	2003Q1	2003Q4	2010Q1	2010Q3
	2008Q4	2009Q3		
	2017Q4	2018Q3		
Germany	2005Q3	2006Q1	2004Q3	2005Q1
	2007Q2	2008Q2	2006Q3	2006Q4
	2012Q1	2012Q2	2012Q4	2014Q1
	2015Q1	2015Q2		
Greece	2005Q4	2006Q4	2009Q1	2009Q4
	2007Q3	2008Q2	2010Q2	2011Q2
			2014Q1	2015Q3
Hungary	2003Q1	2003Q4	2002Q1	2002Q3
	2004Q4	2005Q3	2006Q4	2007Q3
	2017Q1	2017Q3	2009Q4	2010Q1
			2012Q3	2012Q4
India	2002Q3	2002Q4	2008Q3	2009Q3
	2003Q2	2004Q1	2014Q1	2014Q2
	2004Q4	2005Q3	2016Q1	2016Q4
	2006Q4	2008Q2		
	2017Q4	2018Q1		
Indonesia	2009Q4	2011Q2	2008Q1	2008Q2
			2009Q2	2009Q3

Table 8 (continued)

	Net Flow Surge		Net Flow Stop	
	Start	End	Start	End
			2011Q4	2012Q2
			2015Q3	2016Q1
Ireland	2005Q1	2005Q2	2008Q4	2009Q3
	2007Q2	2008Q3	2018Q2	2018Q3
	2011Q1	2011Q2		
	2014Q3	2014Q4		
	2017Q2	2017Q4		
Israel	2007Q1	2007Q4	2005Q3	2006Q2
	2008Q4	2009Q3	2010Q2	2010Q3
	2016Q1	2016Q2	2012Q2	2012Q3
Italy	2002Q4	2003Q3	2004Q2	2004Q4
	2010Q4	2011Q2	2010Q1	2010Q2
	2017Q4	2018Q4	2011Q4	2012Q4
Japan	2003Q3	2004Q2	2004Q4	2005Q3
	2011Q3	2012Q2	2014Q3	2016Q3
	2017Q3	2017Q4		
Korea	2009Q3	2010Q2	2001Q1	2001Q3
	2017Q1	2018Q4	2007Q3	2008Q2
			2008Q4	2009Q1
Mexico	2007Q4	2008Q4	2002Q3	2002Q4
	2010Q4	2011Q3	2009Q3	2009Q4
			2012Q2	2012Q3
			2015Q1	2015Q4
Netherlands	2001Q1	2001Q2	2003Q2	2004Q3
	2005Q2	2005Q4	2009Q1	2009Q4
	2007Q4	2008Q3	2016Q3	2017Q1
	2015Q2	2016Q1		
New Zealand	2005Q2	2005Q3	2008Q3	2009Q3
	2010Q1	2010Q2	2011Q1	2011Q2
	2012Q1	2012Q2		
Norway	2002Q2	2003Q2	2001Q1	2001Q4
	2009Q4	2010Q1	2008Q3	2009Q1
	2012Q4	2013Q2	2011Q3	2012Q2
Poland	2004Q1	2004Q3	2001Q4	2002Q2
	2005Q4	2006Q3	2005Q1	2005Q3
	2007Q2	2008Q3	2009Q1	2009Q3
	2016Q3	2017Q1	2011Q3	2012Q2
			2017Q3	2017Q4
Portugal	2004Q3	2005Q3	2002Q4	2003Q4
	2008Q2	2008Q3	2009Q2	2009Q4
	2014Q4	2015Q3	2011Q1	2012Q2
Russia	2001Q3	2002Q2	2008Q2	2009Q3

Table 8 (continued)

	Net Flow Surge		Net Flow Stop	
	Start	End	Start	End
	2007Q1	2007Q4		
	2009Q4	2010Q3		
	2015Q4	2016Q3		
South Africa	2004Q4	2005Q3	2008Q3	2009Q2
	2018Q2	2018Q3	2015Q3	2016Q1
Spain	2004Q4	2005Q4	2009Q1	2010Q1
	2008Q1	2008Q2		
	2014Q2	2015Q2		
Sweden	2007Q4	2009Q1	2002Q2	2002Q3
	2014Q2	2014Q3	2003Q4	2004Q3
	2016Q1	2016Q3	2010Q3	2010Q4
			2015Q2	2015Q3
			2017Q2	2018Q1
Thailand	2005Q2	2005Q3	2003Q3	2003Q4
	2008Q1	2008Q2	2007Q1	2007Q4
	2010Q2	2011Q1	2009Q1	2009Q2
	2012Q4	2013Q2	2011Q4	2012Q2
			2014Q1	2014Q2
Turkey	2005Q4	2006Q2	2001Q2	2001Q4
	2010Q2	2011Q2	2007Q1	2007Q3
			2008Q4	2009Q4
			2014Q1	2014Q4
			2018Q3	2018Q4
United Kingdom	2003Q3	2004Q4	2005Q1	2005Q3
	2007Q4	2008Q4	2009Q1	2010Q3
	2013Q1	2013Q4		
	2016Q1	2016Q2		
United States	2001Q1	2001Q2	2001Q4	2002Q2
	2006Q1	2006Q3	2007Q3	2008Q2
	2011Q1	2011Q2	2009Q2	2010Q1

Ireland has a net flow surge episode which ends by 2001Q1 which is not included in the list above

Table 9 Credit Growth Volatility and MaPP: Alternative Volatility Measures

Panel	Dependent Variable		Full Sample	AE	EME
A	Credit Growth Volatility (**4** quarters)				
		MaPP	−0.075**	−0.087*	−0.115**
			(−2.10)	(−1.95)	(−2.02)
B	Credit Growth Volatility (**8** quarters)				
		MaPP	−0.010	−0.061**	−0.023
			(−0.51)	(−2.03)	(−0.78)
C	Credit Growth Volatility (**20** quarters)				
		MaPP	−0.013	−0.047***	−0.009
			(−1.12)	(−2.97)	(−0.53)
# of Observations			2285	1437	848
# of Countries			36	22	14

This table presents the estimation results from Eq. (1). The dependent variable is credit growth volatility. t statistics in parentheses

$*p < 0.10$; $**p < 0.05$; $***p < 0.01$

Table 10 Credit Growth Volatility and Individual Policy Instruments

Dependent variable is credit growth volatility			
	Full Sample	AE	EME
Panel A: Aggregate Policy Index			
MaPP	−0.075**	−0.087*	−0.115**
	(−2.10)	(−1.95)	(−2.02)
Panel B: Disaggregated Policy Indices			
$\text{MaPP}^{\text{demand}}$	0.103	−0.016	0.105
	(1.04)	(−0.10)	(0.57)
$\text{MaPP}^{\text{supply}}$	−0.106**	−0.111*	−0.140**
	(−2.43)	(1.87)	(−2.09)
$\text{MaPP}^{\text{rest}}$	−0.154	−0.124	−0.334
	(−0.89)	(−0.80)	(−0.96)
Panel C: Individual Policy Instruments			
DEMAND			
Limits on Debt-Service-to-Income Ratio	−0.271	−0.995***	−0.027
	(−1.35)	(−3.05)	(−0.07)
Limits on Loan-To-Value Ratio	0.150	0.260	−0.005
	(0.98)	(1.34)	(−0.02)
SUPPLY			
Capital Requirements	−0.208*	−0.048	−0.348
	(−1.68)	(−0.33)	(−1.55)
Conservation	−0.325	−0.137	−0.591
	(−1.49)	(−0.66)	(−1.12)

GCRIS

Table 10 (continued)

Dependent variable is credit growth volatility			
	Full Sample	AE	EME
Countercyclical Buffers	−0.221	−0.344	0.438
	(−0.53)	(−0.93)	(0.25)
Leverage Limits	−0.394	−0.313	−0.256
	(−1.04)	(−0.62)	(−0.41)
Systemically Important Financial Institution (SIFI)	0.095	−0.070	0.333
	(0.37)	(−0.29)	(0.49)
Limits on Foreign Exchange Positions	−0.290		−0.330
	(−1.01)		(−0.83)
Liquidity Requirements	−0.208	−0.306**	−0.247
	(−1.55)	(−2.07)	(−0.95)
Reserve Requirements	−0.185**	0.126	−0.249**
	(−2.09)	(0.50)	(−1.97)
Limits on Credit Growth	−1.052	−0.664	−1.360
	(−1.36)	(−0.47)	(−0.96)
Limits on Foreign Currency	0.135	−0.082	0.141
	(0.37)	(−0.16)	(0.21)
Loan Loss Provisions	0.385	−0.315	0.591*
	(1.59)	(−0.64)	(1.76)
Loan Restrictions	0.610**	0.668***	0.520
	(2.35)	(2.56)	(1.10)
REST			
Limits on the Loan-to-Deposit Ratio	−1.037*		−0.897
	(−1.72)		(−1.13)
Tax Measures	0.116	0.015	0.286
	(0.42)	(0.06)	(0.56)
Other	−0.222	−0.225	−0.509
	(−0.94)	(−1.05)	(−0.75)
# of Observations	2285	1437	848
# of Countries	36	22	14

This table presents the estimation results from Eq. (1). The dependent variable is credit growth volatility. Limits on foreign exchange positions and limits on the loan-to-deposit ratios are time-invariant over the AE estimation sample and have been omitted from the estimation. t statistics in parentheses

$*p < 0.10$; $**p < 0.05$; $***p < 0.01$

Table 11 Credit Surge/Stop Episodes, Net Capital Flows and Individual Policy Instruments

	Credit Stop			Credit Surge		
	Full Sample	AE	EME	Full Sample	AE	EME
Panel A: Aggregate Policy Index						
MaPP	0.467***	0.310***	0.807	0.760**	1.075	0.571***
	(−4.74)	(−3.59)	(−1.07)	(−2.18)	(0.37)	(−3.09)
Panel B: Dis-aggregated Policy Indices						
$MaPP^{demand}$	1.133	0.528	1.618	0.318***	0.163***	0.394
	(0.26)	(−0.75)	(0.86)	(−2.67)	(−2.56)	(−1.61)
$MaPP^{supply}$	0.434***	0.192***	0.872	0.933	1.715**	0.617**
	(−4.48)	(−3.84)	(−0.61)	(−0.49)	(2.36)	(−2.37)
$MaPP^{rest}$	0.165**	1.781	0.013***	0.242**	0.238*	0.294
	(−2.34)	(0.58)	(−3.15)	(−2.20)	(−1.74)	(−1.16)
Panel C: Individual Policy Instruments						
DEMAND						
Limits on Debt-Service-to-Income Ratio	0.416	0.000**	2.011	0.227	0.057**	0.327
	(−0.76)	(−2.27)	(0.56)	(−1.62)	(−2.01)	(−0.91)
Limits on Loan-To-Value Ratio	2.624	3.739	2.921	0.247**	0.149**	0.144*
	(1.34)	(1.14)	(1.11)	(−2.09)	(−1.96)	(−1.88)
SUPPLY						
Capital Requirements	0.781	0.573	1.042	7.257***	9.203***	6.200***
	(−0.43)	(−0.49)	(0.05)	(4.81)	(3.79)	(2.86)
Conservation	1.100	0.522	4.768	1.032	8.921**	0.004***
	(0.09)	(−0.37)	(1.03)	(0.04)	(2.16)	(−2.87)
Countercyclical Buffers	0.000***	0.013	0.000*	0.020**	0.019**	5.12×10^{21}
	(−3.06)	(−0.79)	(−1.93)	(−2.20)	(−2.03)	(0.01)
Leverage Limits	0.256	0.002	0.175	0.277	4.278	0.213
	(−0.76)	(−0.97)	(−0.86)	(−0.92)	(0.76)	(−0.71)
Systemically Important Financial Institution (SIFI)	0.075*	0.020	0.294	4.997*	1.642	206.207***
	(−1.81)	(−1.41)	(−0.65)	(1.76)	(0.44)	(2.77)
Limits on Foreign Exchange Positions	31.266***		18.356**	0.003***		0.003***
	(2.63)		(2.18)	(−4.45)		(−4.15)
Liquidity Requirements	0.212**	0.133	0.539	0.380*	0.412	0.367
	(−2.49)	(−1.62)	(−0.80)	(−1.77)	(−1.31)	(−1.02)
Reserve Requirements	0.724	0.745	0.929	0.816	503.32	0.630
	(−0.82)	(−0.28)	(−0.17)	(−0.61)	(1.53)	(−1.31)
Limits on Credit Growth	0.000***	0.000	0.000**	0.000**	0.000	0.000**
	(−2.62)	(−0.01)	(−2.08)	(−2.42)	(−0.01)	(−2.46)
Limits on Foreign Currency	0.372	0.002**	4.629	0.047*	0.000	1.350
	(−0.70)	(−2.02)	(0.84)	(−1.71)	(−0.02)	(0.14)
Loan Loss Provisions	0.062**	0.268	0.022**	0.128**	0.004***	0.478
	(−2.03)	(−0.42)	(−2.32)	(−2.24)	(−2.93)	(−0.72)
Loan Restrictions	0.412	0.111	0.787	1.428	5.951	0.234

Table 11 (continued)

	Credit Stop			Credit Surge		
	Full Sample	AE	EME	Full Sample	AE	EME
	(−0.79)	(−1.12)	(−0.16)	(0.36)	(1.32)	(−0.93)
REST						
Limits on the Loan-to-Deposit Ratio	0.018		0.021	5.513		9.456
	(−1.47)		(−1.38)	(0.76)		(0.96)
Tax Measures	0.003***	0.093	0.000***	0.078**	0.097*	0.005*
	(−3.24)	(−1.04)	(−3.02)	(−2.31)	(−1.76)	(−1.77)
Other	0.616	5.512	0.159	0.169*	0.231	0.248
	(−0.49)	(1.38)	(−0.93)	(−1.86)	(−1.24)	(−0.76)

This table presents the estimation results from Eq. (2). The dependent variable is a dummy variable indicating if there is a credit growth episode (surge, stop, or normal). Limits on foreign exchange positions and limits on the loan-to-deposit ratios are time-invariant over the AE estimation sample and have been omitted from the estimation. Exponentiated coefficients (relative risk ratios - RRR); t statistics in parentheses

$*p < 0.10$; $**p < 0.05$; $***p < 0.01$

Table 12 Effectiveness of MaPP with Alternative Surge/Stop Definitions

	Credit Stop			Credit Surge		
	Full Sample	AE	EME	Full Sample	AE	EME
Panel A: Forbes and Warnock (2012) Definitions (Benchmark)						
MaPP	0.467***	0.310***	0.807	0.760**	1.075	0.571***
	(−4.74)	(−3.59)	(−1.07)	(−2.18)	(0.37)	(−3.09)
Panel B: Forbes and Warnock (2012) Definitions with Alternative Threshold Values						
Threshold Value = 1.7 × standard deviation						
MaPP	0.446***	0.291***	0.792	0.772**	1.145	0.594***
	(−4.85)	(−3.64)	(−1.12)	(−1.98)	(0.67)	(−2.76)
Threshold Value = 2 × standard deviation						
MaPP	0.387***	0.225***	0.799	0.621***	1.027	0.466***
	(−5.33)	(−4.10)	(−1.00)	(−3.20)	(0.11)	(−3.77)
Panel C: Ghosh et al. (2014) Definition						
MaPP	0.691**	0.239***	1.107	0.314***	0.014***	0.721*
	(−2.34)	(−5.38)	(0.42)	(−6.65)	(−6.25)	(−1.74)

This table presents the estimation results from Eq. (2). The dependent variable is a dummy variable indicating if there is a credit growth episode (surge, stop, or normal). Limits on foreign exchange positions and limits on the loan-to-deposit ratios are time-invariant over the AE estimation sample and have been omitted from the estimation. Exponentiated coefficients (relative risk ratios - RRR); t statistics in parentheses

$*p < 0.10$; $**p < 0.05$; $***p < 0.01$

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