

Leakages from macroprudential regulations: The case of household-specific tools and corporate credit *

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Abstract

Sector-specific macroprudential regulations increase the riskiness of credit to other sectors. Using firm-level data, we construct measures of the riskiness of corporate credit allocation for 29 advanced and emerging economies. Consistently across these measures, we find that an unexpected tightening of household-specific macroprudential tools is followed by a rise in riskier corporate lending, and more so during credit expansions. Quantitatively, such unexpected tightening during a period of rapid credit growth increases the riskiness of corporate credit by around 10 percent of the historical standard deviation. This result supports early policy interventions when credit vulnerabilities are still low, since sectoral leakages will be less important at this stage. Further evidence from bank lending standards surveys suggests that the leakage effects are stronger for larger firms compared to SMEs, consistent with recent evidence on the use of personal real estate as loan collateral by small firms.

JEL Classification: G21, G28, G38

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1 Introduction

Macroprudential policies can have indirect effects on the economy beyond the direct impact on the lenders or borrowers they target. The literature on cross-border spillovers of financial regulations has documented that a tightening of regulations in the home country can lead to more and riskier lending by international banks in host countries (Houston, Lin and Ma (2012), Ongena, Popov and Udell (2013)). In the macroprudential context, regulations limiting foreign-currency (FX) borrowing by banks lead to higher FX debt issuance by nonfinancial private corporations (Ahnert et al. 2020).

In this paper we provide evidence on another type of indirect effects of financial regulations: leakages from sector-specific macroprudential policies to borrowers in other sectors. Cross-sectoral credit and risk substitution from macroprudential regulations can happen through various channels. For example, if lenders operate under lender-specific targets for returns or lending, or under fixed risk appetite, they could “compensate” a tightening of regulations in one loan segment by increasing targets in other segments. As a result, they could end up lending to borrowers that otherwise would be perceived as too risky. Alternatively, if a macroprudential action in one overheating sector leads to a perception of reduced risks in the economy, this could induce agents in other sectors to take on more risk. Bengui and Bianchi (2018) present a model where regulated agents reduce risk taking in response to debt taxes, but unregulated agents react to the safer environment by engaging in more risky activities.

From the policy perspective, estimates of such leakage and substitution effects could inform the choice between broad-based and targeted macroprudential tools. Yet, empirical evidence so far has been limited to few case studies (including Auer and Ongena (2016) and Acharya, Bergant, Crosignani, Eisert and McCann (2020)), making it difficult to generalize conclusions to a broad range of macroprudential policies. Our contribution is to fill this gap by providing evidence of leakages from sector-specific macroprudential tools across a large group of advanced and emerging economies, and by quantifying their magnitude.¹

Given their relatively broad adoption, we focus on macroprudential policies targeting borrowing by households, such as loan to income (LTI), loan to value (LTV) or debt service to income (DSTI) limits and study the impact such measures can have on lending to non-financial corporations. Specifically, we are interested in the question whether a tightening in household-specific macroprudential tools increases the risk profile of corporate credit. Using firm-level data for a range of advanced (AEs) and emerging market economies (EMs), we construct three country-level measures of *riskiness of corporate credit allocation* that are based on the relative riskiness of firms taking on a lot of new debt (both bank loans and market financing) com-

¹By “leakages” we mean changes in the risk profile of borrowers in the sectors that are not directly targeted by a macroprudential policy change. We do not distinguish here between intended and unintended effects. For example, a shift of risk from a sector with a high level of financial vulnerabilities to a sector where those vulnerabilities are contained, in certain instances could be a desirable outcome from the perspective of policymakers.

pared to firms that do not increase their debt financing or increase it very little. As shown in Greenwood and Hanson (2013), International Monetary Fund (2018) and in Brandão-Marques et al. (2019), such measures of the riskiness of credit allocation predict i) performance of bond returns, ii) episodes of financial instability, and iii) downside risks to growth; they also signal a forthcoming crisis better than the underlying conventional corporate vulnerability indicators when considered individually.

Consistently across the three measures, we find that an unexpected tightening of household-specific macroprudential tools increases the riskiness of corporate credit allocation in a country and that this effect is more pronounced during credit expansions.² Quantitatively, following such unexpected tightening, corporate credit riskiness increases by 10 percent of a standard deviation when credit to GDP growth is one standard deviation above its sample mean. In terms of policy implications, our results support policy interventions during the early phase of the credit expansion cycle when vulnerabilities are low and sectoral leakages are less important. The results are robust to controlling for domestic and global financial conditions, controlling for housing booms, excluding outliers, applying local projections, using different definitions of macroprudential policies, and using policy changes instead of policy shocks.

Finally, when instead of the riskiness of corporate credit allocation we look at the changes in bank lending standards reported in loan officer surveys, we find that a tightening in the household-specific macroprudential policies is followed by a relaxation of lending standards for loans to large corporations, but by a tightening of lending standards for small- and medium-size enterprises (SMEs). The latter finding is consistent with the evidence that owners of SMEs oftentimes use personal real estate as collateral for firm loans (Adelino, Schoar and Severino (2016), Bahaaj et al. (2019)).

The rest of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 looks at the data sources and explains the construction of the macroprudential indexes and the corporate riskiness indicators. Section 4 visits the regression framework adopted. Section 5 explains the results and Section 6 concludes.

2 Literature

Past research has primarily focused on the impact of macroprudential policies on credit and house price growth. Kuttner and Shim (2016) find that a tightening of DSTI limits lowers the housing credit growth rate, and that an increase in the housing-related taxes lowers both housing credit and house price growth. The results in Cerutti, Claessens and Laeven (2017) suggest that the use of macroprudential policies has significant mitigating effects on real credit growth,

²Since macroprudential policies are often deployed in response to (or in order to prevent) increasing vulnerabilities, we derive macroprudential policy shocks following a procedure akin to Forbes and Klein (2015) and Ahnert et al. (2020), and use those in the baseline regressions.

especially for emerging economies and economies with relatively closed capital accounts. They also suggest a higher effectiveness of these policies in the boom than in the bust phase of financial cycles and find evidence of cross-border borrowing as a potential channel of regulatory evasion. Akinci and Olmstead-Rumsey (2018) find that periods of macroprudential policy tightening are associated with slower bank credit growth, slower house credit growth and smaller house price appreciation. Additionally, household sector-specific policies like LTV and DSTI limits are more important for constraining house price appreciation when bank lending is an important source of credit. Alam et al. (2019) find that the effect of a tightening of LTV limits on household credit growth is non-linear in the size of the tightening and in the initial LTV limit level. Araujo et al. (2020) provide a metadata analysis of the findings across over 50 studies analyzing effectiveness of macroprudential policies.

Several papers have looked at leakages from macroprudential policies. Especially post-GFC, there has been substantial interest in arbitrage of domestic regulations through cross-border activities. Houston, Lin and Ma (2012) use a cross-country study to show that capital flows from markets with more restrictive regulations to markets with loose regulation. Ongena, Popov and Udell (2013) find that domestic banking regulations have significant spillovers through cross-border banking activities. Stricter domestic regulations result in lower lending standards in foreign markets, which are further lowered if the domestic supervision is inefficient. Aiyar, Calomiris and Wieladek (2014) provide evidence of regulatory arbitrage in the U.K., where regulatory tightening leads to a contraction in loan supply by domestic banks but to an expansion of loan supply by subsidiaries of foreign banks. Using bank-level data for the U.K., Danisewicz, Reinhardt and Sowerbutts (2017) show that increased capital requirements result in a contraction of international bank lending, and that this effect is amplified by unconventional policies aimed at bolstering domestic lending. Ahnert et al. (2020) find that although macroprudential FX regulations are effective in reducing foreign currency borrowing by banks, FX-related risks are partially shifted to the corporate sector through increased FX bond issuance. Temesvary (2018) finds that as host countries' regulations became more restrictive relative to the U.S. during 2003-2013, global U.S. banks substituted from lending through local affiliates in host countries to more direct cross-border lending.

The existing empirical evidence on the leakages from sector-specific macroprudential policies to other types of borrowers is limited to few case studies. For example, Auer and Ongena (2016) exploit variation in banks exposure to the housing sector to study the impact that a countercyclical buffer against mortgage exposures introduced in Switzerland in 2012 had on banks lending profiles. They find that banks with a higher share of residential risk-weighted assets relative to total assets lent more to corporations than banks with a lower share, and that banks shifted lending to riskier and smaller firms following the introduction of the buffer. Acharya et al. (2020) use supervisory loan-level and house price data from Ireland and find that banks more affected by the introduction of LTI and LTV limits on residential mortgages

in 2015 increased their holdings of high-yield securities and increased lending to the corporate sector (at lower rates). For both papers, however, the case-specific character of the micro-level analysis raises questions whether conclusions from such studies can be generalized to other macroprudential policies.

Closely related to our analysis is a paper by Ayyagari, Beck and Martinez-Peria (2018), who look at the effects of macroprudential policies by firm size and age. They find that borrower-based macroprudential tools slow down credit growth of corporates, but predominantly for micro firms, SMEs and young firms. In our analysis, we show that lending standards for SMEs tighten after a tightening of LTV, DSTI or other household-specific measures, but that at the same time lending standards for loans to large corporations are eased.³

Finally, in constructing the measures of corporate credit riskiness, we build on the approach by Greenwood and Hanson (2013), International Monetary Fund (2018) and Brandão-Marques et al. (2019) –see Section 3 for details. Other papers on credit riskiness include Kirti (2020), who constructs a measure of lending standards based on primary debt capital markets data and finds it to closely follow survey measures of bank lending standards. We use bank lending surveys as a robustness check for our results.

3 Data

Measuring corporate credit riskiness. We construct measures of riskiness of corporate credit allocation following Greenwood and Hanson (2013). Their key insight is that cyclical changes in the pricing of credit risk disproportionately affect financing costs faced by low-quality firms compared to high-quality firms. Thus, to the extent that firms issue more debt when it is cheap, the time-variation in debt issuer quality may be useful for monitoring financing conditions and credit vulnerabilities. Greenwood and Hanson (2013) measure the riskiness of corporate credit as the difference in the expected default frequency (EDF) between the top 20 percent of debt issuers among NYSE-listed firms and the bottom 20 percent of debt issuers among the listed firms and show that it is a more reliable signal of credit market overheating than rapid credit growth. This result holds also when using differences in leverage and the interest coverage ratio (ICR) among debt issuers instead of the EDF. Acharya et al. (2016) follow a similar approach, and measure riskiness using the ICR. International Monetary Fund (2018) analyze four measures of riskiness in the corporate sector: based on EDF, ICR, leverage, and using an indicator for debt overhang.

Following this literature, we consider three measures of riskiness of corporate credit allocation, based on three indicators of firm-level financial vulnerability:

³One channel could be the use of personal real estate as collateral to finance small firms as in Gelos and Werner (2002) and Adelino, Schoar and Severino (2016). Lian and Ma (2020) show, for the U.S., that asset-based (collateralized) loans are more common among small and young firms, compared to large and old corporates who rely more on cash flow-based loans.

- **leverage-based measure (TDTA hereafter)**, constructed by calculating the difference in the ratio of total debt to total assets of top 20 percent debt issuers over the current quarter and the bottom 20 percent debt issuers among listed firms,
- **debt overhang measure (TDtE)**, constructed as above, but using the ratio of total debt to earnings before interest, taxes, depreciation and amortization (EBITDA) instead of total debt to total assets ratio,
- **interest coverage ratio measure (ICR)**, constructed as above but using the interest coverage ratio, defined as the ratio of interest expenses to EBITDA.

For each vulnerability indicator (TDTA, TDtE, ICR), each firm is assigned a value (from 1 to 10) according to the decile of the distribution of the indicator in a given quarter and the country of location. Next, the firms are sorted in a similar way according to the change in the net debt over the past year relative to past total assets. Debt includes both loans and bond financing. A riskiness of corporate credit allocation measure is computed as the difference in the average value of the vulnerability indicator for the top debt-takers (assigned values 9 or 10 for the change in net debt) and the average value of the vulnerability indicator for the bottom debt-takers (assigned values 1 and 2).⁴ It follows that the riskiness measures increase (decline) whenever the average vulnerability indicators increase more (increase less or decline) among top debt-takers relative to bottom debt-takers.

All firm-level data come from Datastream. We drop all firms classified as financial, insurance or public administration companies. When constructing the measures of riskiness, we impose a condition of a minimum of 30 firm observations in each quarter for each country.⁵ To remove composition effects resulting from reporting on a lower than quarterly frequency by some firms, we seasonally-adjust all the series. Following the above procedure, we construct the measures of riskiness of corporate credit allocation for 29 economies (13 advanced plus 16 emerging) on a quarterly frequency (Table 1).⁶ The sample is unbalanced, with data for majority of economies going back until 2002.

Table (1) *Riskiness of corporate credit allocation: Country sample.*

Advanced Economies	Emerging Markets and Developing Economies
Austria, Canada, Denmark, Finland Germany, Israel, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden	Argentina, Brazil, Bulgaria, Chile, China, Indonesia, South Korea, Malaysia, Mexico, Peru, Philippines, Poland, Russia, Thailand, Turkey, Vietnam

⁴Using deciles instead of raw values of vulnerability indicators minimizes the influence of outliers, and prevents the possibility of picking up secular trends affecting the results.

⁵Country-level correlations between the riskiness measures constructed using the threshold of 30 firms and the riskiness measures constructed using a higher threshold of 40 firms do not fall below 0.95. Given this, we use the threshold of 30 as it increases somewhat the number of observations in the sample.

⁶For additional 8 countries we were able to construct biannual time series.

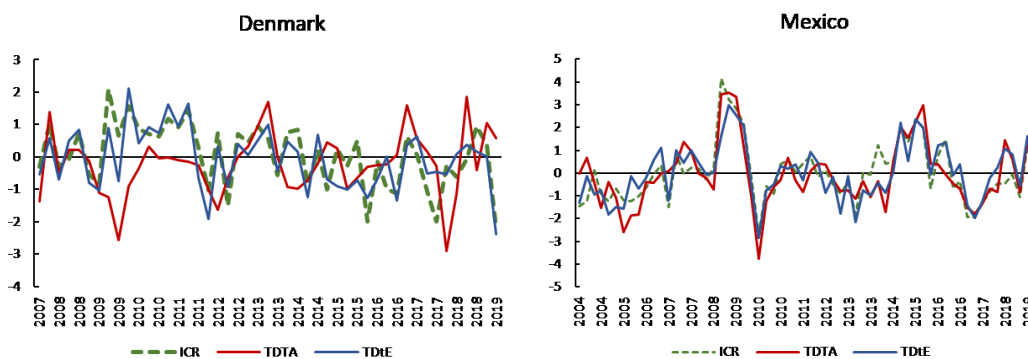
The correlation between the three alternative measures is high (highest for ICR and TDtE given similar definitions), although it varies somewhat across countries (Table 2). Figure 1 shows time series of TDTA, TDtE and ICR based measures for two countries: Denmark and Mexico. After Sweden, Denmark is the country with second-lowest correlation between leverage-based and the TDtE and ICR measures (of 0.12), while Mexico has a relatively high correlation (of 0.81).

International Monetary Fund (2018) construct the above three measures also using Datstream data but on annual frequency, which allows them to expand the sample to mid-1990s. They find that an increase in the riskiness of credit allocation measures signals heightened downside risks to GDP growth and a higher probability of banking crises and banking sector stress, over and above the previously documented signals provided by credit growth. Thus, a riskier allocation of corporate credit is an independent source of financial vulnerability.

Table (2) *Correlations between the riskiness of corporate credit allocation measures (cross-country averages).*

	TDTA	TDtE	ICR
TDTA	1		
TDtE	0.5	1	
ICR	0.38	0.79	1

Figure (1) *Evolution of the riskiness of corporate credit allocation in Denmark and Mexico (quarterly frequency, seasonally adjusted, demeaned).*



Macroprudential policies. We use the IMF iMaPP database as a source of information on macroprudential policy actions (MaPPs).⁷ The database reports macroprudential policy actions by the sector targeted by the measure (broad-based, household sector, corporate sector) on a quarterly frequency from mid-1990s until 2018Q4. Each policy change is recorded as +1 if it was a tightening action, and as -1 if it was an easing action. A zero is recorded if there was no policy change. We construct two MaPP policy indicators based on the iMaPP database:

⁷See Alam et al. (2020) for a description of the database.

- The household sector-targeting macroprudential policy actions indicator, $MaPP^{HH}$. We use the sum of changes in the four most widely used measures in literature, Loan to Value (LTV), Loan to Income (LTI), Debt to Income (DTI) and Debt Service to Income (DSTI) limits as our baseline measure. When conducting robustness exercises, we also use a broader indicator, $MaPP^{HH}(\text{Alternate})$, which is sum of changes in LTV, LTI, DTI, DSTI limits and restrictions on household loan characteristics.
- The broad-based plus corporate sector-specific macroprudential policy actions indicator, $MaPP^{BC}$. It includes changes in bank capital requirements (general and corporate-specific), changes in the countercyclical capital buffer, limits on credit growth (overall and corporate-specific) and restrictions on corporate loans characteristics. As a robustness check, we also use a narrower measure $MaPP^{BC}(\text{Alternate})$, that captures changes in the countercyclical capital buffer, limits on credit growth (overall and corporate sector specific) and restrictions on corporate loan characteristics.

Overall, in the sample of 29 economies for which we were able to construct the riskiness of corporate credit allocation measures, we document 120 changes in baseline measures of household-specific MaPPs, and 66 changes in baseline measures of the broad-based and corporate-specific MaPPs between 2002Q1-2018Q4. Importantly, there is little overlap between the two types of macroprudential interventions: changes in household-specific macroprudential measures are not highly correlated with changes in the broad-based or corporate-specific tools (Table 3).

Table (3) *Number of macroprudential policy actions (easings or tightenings): 2002Q1-2018Q4 (29 countries).*

MaPP actions	Overlapping policy actions		Total BC actions
	<i>HH</i> (Baseline)	<i>HH</i> (Alternate)	
<i>BC</i> (Baseline)	5	13	66
<i>BC</i> (Alternate)	5	11	26
Total HH actions	120	169	-

Figure 2 shows that macroprudential policies have been used relatively more in EMs relative to AEs in our sample. For both types of MaPPs, the number of actions (tightening and easing) in EMs are almost double the number of actions in AEs. Separately, MaPP policies were tightened more often (154) as compared to eased (34) during the sample period. Moreover, household-specific MaPPs were used more frequently than the broad-based or corporate-specific measures. Figure 3 shows the evolution of the policy actions in EMs and AEs by year. EMs tightened much more compared to advanced economies during the Global financial crisis period. 2018 saw a number of advanced economies tightening LTV and DSTI limits.

Figure (2) *Number of macroprudential policy changes between 2002Q1 and 2018Q4.*

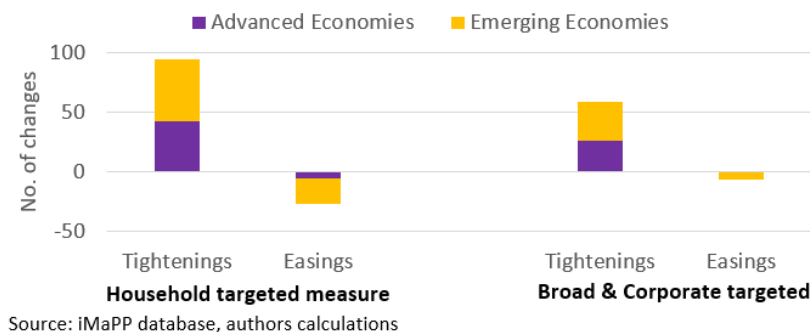
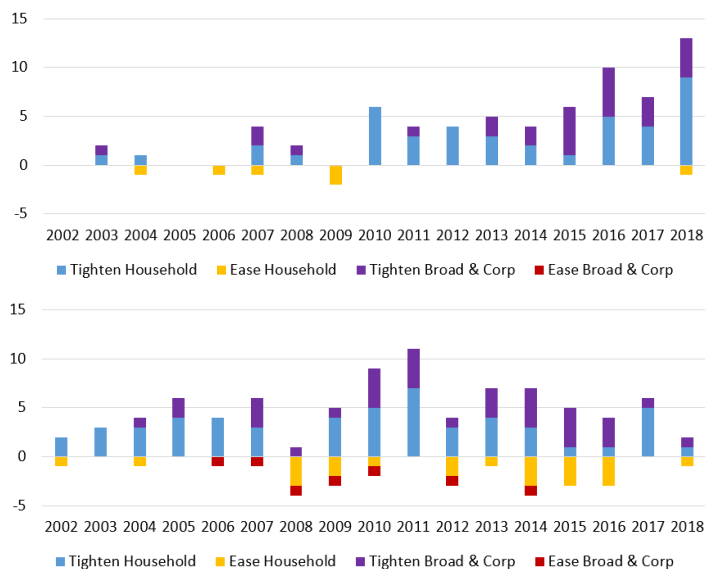


Figure (3) *Use of macroprudential policies in advanced (top) and emerging economies (bottom)*



Macroprudential shocks. To address potential endogeneity issues, several papers studying macroprudential (or other financial) regulations consider shocks to macroprudential policy actions instead of actual policy changes. This is done by applying a two-stage regression procedure where policy functions for MaPPs are estimated first, and where the residuals from such regressions are used as the policy shocks (Forbes and Klein (2015), Ahnert et al. (2020) and Brandao-Marques et al. (2020)).

We expect that the endogeneity issues are less of a concern when considering leakages from macroprudential actions. This is because the decisions to ease or tighten household-specific macroprudential policies are likely to be taken independently of the situation in the corporate sector. Indeed, this is what the small overlap between household-specific and broad-based or corporate-specific MaPPs shown in the Table 3 seems to suggest. Nevertheless, a positive correlation between the corporate credit riskiness and the situation in the local household credit

markets through the credit cycle is very likely. In this case, a tightening of household specific MaPPs in response to vulnerabilities building up e.g. in the housing market could spuriously show up as amplifying risks in the corporate sector as well. Thus, we follow the literature and use macroprudential policy shocks in our baseline regressions. In the Appendix A.5, we show the results are unchanged when using policy actions instead.

We obtain macroprudential shocks as residuals from ordered probit regressions of our indicator variables $MaPP^{HH}$ and $MaPP^{BC}$ on a range of macrofinancial variables: real GDP growth, one-year ahead GDP growth forecast, real credit growth, capital account openness, financial development index, exchange rate change against U.S. dollar, and real house price growth. Appendix A.2 describes the methodology for computation of shocks in detail and shows that the main results are robust to using an alternative specification of the ordered probit regression. The macroprudential shocks are available for a subsample of 24 out of 29 countries. The countries for which we cannot construct macroprudential shocks due to data constraints are Argentina, Bulgaria, Chile, Peru and Vietnam. We include those countries in the robustness regressions when we use macroprudential policy actions instead of policy shocks (Appendix A.5).

Lending Standards. As an additional robustness exercise, we use bank lending standards for corporate loans, as reported in bank loan officer surveys, instead of the corporate riskiness measures. Importantly, lending standards data can be further disaggregated into SMEs and large corporations, allowing us to estimate the leakage effects by the firm size. The data come from the ECB and national authorities and was collected through Haver Analytics and are available for 15 countries for which we also can construct macroprudential policy shocks (Austria, Canada, Germany, Italy, Japan, Korea, Netherlands, Norway, Philippines, Poland, Portugal, Russia, Spain, Thailand and Turkey) and goes back to 2002-2004 for most of the countries.⁸ The shortest time series are available for Thailand (2007Q4), Norway (2008Q1), Philippines (2009Q1), Russia (2009Q2). Given the considerable reduction in the sample size when using bank lending standards, we treat the three measures of the riskiness of corporate credit allocation as our baseline measures.

Other variables. We take GDP growth rates and exchange rates from WEO database. Data on domestic credit to GDP, on domestic corporate bond issuance and domestic bank credit to the corporate sector come from the BIS. The country-specific financial conditions indices (FCI) are taken from the IMF.⁹ As an alternative measure of the domestic financial stance we use 3-month money market rates from Datastream. The global variables (MSCI VIX, U.S. policy rates) are from Datastream and Wu and Xia (2016). Data on GDP growth forecasts, financial development index, and capital account openness used in the first-stage regressions when deriving macroprudential policy shocks come from Consensus forecasts, IMF, and IMF's

⁸For Norway and Canada the surveys do not distinguish firms by size.

⁹See International Monetary Fund (2017) and Koop and Korobilis (2014) for details.

AREAER report, respectively. Table A1 in the Appendix A.1 lists all data sources.

4 Empirical Specification

We apply multi-country panel regressions to study the impact of household-specific macroprudential policy changes on the riskiness of corporate credit allocation. The baseline regression specification takes the following form:

$$CC_{i,t}^s = \alpha + \gamma CC_{i,t-1}^s + \sum_{k=1}^4 \beta_{1,k} \varepsilon_{i,t-k}^{HH} + \sum_{k=1}^4 \beta_{2,k} \varepsilon_{i,t-k}^{BC} + \beta_3 X_{i,t-1} + \delta_i + \delta_t + \epsilon_{i,t}, \quad (1)$$

where $CC_{i,t}^s$ is a measure $s \in \{\text{TDTA}, \text{TDtE}, \text{ICR}\}$ of corporate credit riskiness in country i in quarter t and where $\varepsilon_{i,t-k}^{HH}$ and $\varepsilon_{i,t-k}^{BC}$ are macroprudential (household specific and broad-based or corporate specific) policy shocks in quarter $t-k$. A positive (negative) coefficient on a MaPP variable would suggest that an unexpected tightening of policy is associated with an increase (decline) in the riskiness of corporate credit allocation. $X_{i,t-1}$ is a vector of control variables. In the baseline specification, it includes i) quarterly year-on-year growth in the credit-to-GDP ratio as a measure of the stance of the credit cycle, ii) quarterly year-on-year real GDP growth, iii) domestic currency appreciation against U.S. dollar in the previous quarter to control for changes in the riskiness of credit allocation from valuation changes in debt denominated in foreign currency. Finally, δ_i and δ_t denote time and country fixed effects. In all regressions we compute standard errors robust to heteroskedasticity and autocorrelation.

It has been documented that the effectiveness of the macroprudential policy likely depends on the position of the business and credit cycle (e.g. Cerutti, Claessens and Laeven (2017)). To capture such nonlinear effects, we also consider an alternative specification, where the macroprudential policy shocks are interacted with the growth in the credit to GDP ratio. To keep the model tractable and reduce the number of interaction terms, we include only one measure of macroprudential policy shocks, which is the sum of policy shocks in the past four quarters:

$$CC_{i,t}^s = \alpha + \gamma CC_{i,t-1}^s + \beta_1 \bar{\varepsilon}_{i,t-1}^{HH} + \beta_2 \bar{\varepsilon}_{i,t-1}^{HH} \times \Delta Credit_{i,t-1} + \beta_3 \bar{\varepsilon}_{i,t-1}^{BC} + \beta_4 \bar{\varepsilon}_{i,t-1}^{BC} \times \Delta Credit_{i,t-1} + \beta_5 X_{i,t-1} + \delta_i + \delta_t + \epsilon_{i,t}, \quad (2)$$

where $\bar{\varepsilon}_{i,t}^{HH} = \sum_{k=0}^3 \beta_{1,k} \varepsilon_{i,t-k}^{HH}$, $\bar{\varepsilon}_{i,t}^{BC} = \sum_{k=0}^3 \beta_{1,k} \varepsilon_{i,t-k}^{BC}$, and where $\Delta Credit_{i,t}$ stands for year-on-year growth in the credit-to-GDP ratio in country i in quarter t .

5 Results

Before moving to our main results, we first demonstrate that household-specific macroprudential tools are effective in achieving their frequent operational targets i.e. affecting growth

of credit to the household sector and growth of house prices. Table A4 in the Appendix shows that an unexpected household-specific MaPP tightening in the past four quarters reduces house price growth and growth of credit to the household sector, and more so when credit growth has been rapid in the recent past. This is consistent with past literature discussed in Section 2.

5.1 Baseline Results

Results from the baseline specification (1) are shown in columns 1-3 of Table 4. The first lag of riskiness indicators is always positive and statistically significant, indicating high persistence of corporate credit riskiness. Amongst the control variables, the lag of growth of total credit to GDP is positive and highly significant, implying an increase in the riskiness of corporate credit allocation during credit expansions. GDP growth has a similar effect. Appreciation of the domestic currency against the US Dollar does results in a lower TDTA indicator, likely reflecting valuation effects from debt denominated in foreign currency. However, the opposite holds for the ICR indicator.

The first column of Table 4 shows the effect of an unexpected tightening of macroprudential measures on the leverage-based measure of corporate credit riskiness (TDTA). All lags of the household-specific MaPPs are positive, indicating that an unexpected tightening would be associated with an increase in riskiness of corporate credit allocation within a year. The coefficients on broad plus corporate sector-specific MaPP shocks have mixed signs, suggesting no clear association with corporate credit riskiness. However, the four lags of both types of MaPPs are not jointly statistically significant. Columns 2 and 3 of Table 4 show results for the other two riskiness indicators (ICR and TDtE), where the lags of MaPP shocks are again not statistically significant.

The lack of statistical significance of MaPP shocks in equation (1) could be due to missing non-linear effects of MaPPs depending on the stage of the credit cycle. Columns 4-6 of Table 4 show the results of the alternative specification (2), where MaPP shocks are interacted with the credit to GDP growth. While the standalone MaPP terms continue to be insignificant (except for TDtE), the interaction term of the household-specific MaPP shock (in this case a sum of shocks in the past four quarters) with credit to GDP growth is positive and statistically significant for all three credit riskiness measures. Quantitatively, when the growth rate of credit to GDP ratio is equal to the sample average, an unexpected tightening in the household-specific MaPPs over the past year increases the riskiness of corporate credit allocation by about 1 percent of its historical standard deviation on average across measures. At the same time, when domestic credit relative to GDP grows at a rate of one standard deviation above the sample mean, the impact on corporate credit riskiness is around 10 percent of historical standard deviation on average (Figure 4)—implying that the leakages from sector-specific MaPPs can be economically meaningful during credit expansions.

Table (4) *Baseline Regressions*

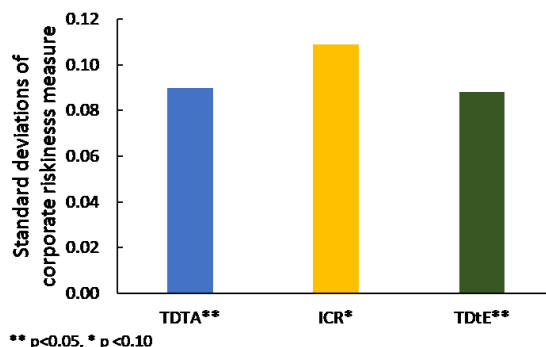
VARIABLES	(1) TDTA	(2) ICR	(3) TDtE	(4) TDTA	(5) ICR	(6) TDtE
$DependentVariable_{t-1}$	0.486*** (0.042)	0.328*** (0.040)	0.385*** (0.037)	0.487*** (0.043)	0.326*** (0.040)	0.381*** (0.037)
ε^{HH} , Lag 1	0.004 (0.041)	-0.061 (0.044)	-0.061 (0.047)			
ε^{HH} , Lag 2	0.057 (0.044)	0.008 (0.046)	-0.044 (0.050)			
ε^{HH} , Lag 3	0.116** (0.044)	-0.012 (0.069)	-0.023 (0.057)			
ε^{HH} , Lag 4	0.004 (0.045)	0.064 (0.044)	0.062 (0.054)			
ε^{BC} , Lag 1	0.064 (0.122)	0.087 (0.117)	0.113 (0.157)			
ε^{BC} , Lag 2	0.096 (0.110)	0.004 (0.112)	0.058 (0.137)			
ε^{BC} , Lag 3	-0.118 (0.119)	-0.080 (0.128)	-0.000 (0.135)			
ε^{BC} , Lag 4	-0.102 (0.097)	-0.156 (0.133)	-0.193 (0.134)			
$\bar{\varepsilon}_{t-1}^{HH}$				0.020 (0.024)	-0.029 (0.032)	-0.067* (0.038)
$\bar{\varepsilon}_{t-1}^{BC}$				0.026 (0.045)	0.019 (0.065)	0.023 (0.078)
$\bar{\varepsilon}_{t-1}^{HH} \times \Delta Credit_{t-1}$				0.012** (0.005)	0.014* (0.007)	0.022** (0.008)
$\bar{\varepsilon}_{t-1}^{BC} \times \Delta Credit_{t-1}$				-0.018* (0.010)	-0.022 (0.019)	-0.015 (0.014)
$\Delta Credit_{t-1}$	0.021*** (0.005)	0.025*** (0.008)	0.032*** (0.007)	0.019*** (0.006)	0.022** (0.009)	0.028*** (0.008)
ΔGDP_{t-1}	0.044*** (0.010)	0.034*** (0.012)	0.057*** (0.015)	0.041*** (0.010)	0.031** (0.012)	0.055*** (0.015)
$\Delta_q ER_{t-1}$	-0.011* (0.005)	0.013* (0.006)	0.009 (0.006)	-0.011** (0.006)	0.012* (0.006)	0.008 (0.006)
Observations	1,257	1,257	1,247	1,257	1,257	1,247
Number of Nat_Code	24	24	24	24	24	24
Adjusted R-squared	0.379	0.169	0.251	0.381	0.173	0.254
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Interaction				Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: $\varepsilon^{HH(BC)}$ is the household-specific (broad-based or corporate-specific) MaPP shock, $\bar{\varepsilon}_{t-1}^{HH(BC)}$ is the sum of shocks in the past four quarters, $\Delta Credit_{t-1}$ is the lagged yoy growth of credit to non-financial private sector relative to GDP, ΔGDP_{t-1} is the lagged yoy Real GDP growth, $\Delta_q ER_{t-1}$ is the lagged qoq local currency appreciation rate against USD.

Figure (4) *Estimated impact of an unexpected tightening of household-specific MaPPs on corporate credit riskiness during credit expansion*



Note: The impact of an unexpected tightening of household-specific MaPPs is computed by dividing the regression coefficients on the interaction term of $\bar{\varepsilon}_{i,t-1}^{HH}$ with $\Delta Credit_{t-1}$ in columns 4-6 in Table 4 by the mean standard deviation of the given riskiness measure, and multiplying the resulting number by the average plus one standard deviation credit to GDP growth rate across countries.

The interaction term of the broad-based or corporate sector-specific MaPP shock with credit to GDP growth, while negative across measures, is statistically significant for the TDTA measure only. This result suggests that the effectiveness of those MaPP measures in reducing riskiness of credit in the corporate sector might be limited—perhaps thanks to the easier access to less regulated (non-bank) sources of funding for corporates compared to households.

5.2 Robustness

We conduct a broad range of robustness exercises. Tables 5-7 present a sample of them, for each of the three credit riskiness measures. Our starting point is the specification (2) that includes the interaction term between the macroprudential variables and the growth rate of the credit to GDP ratio.

Column 1 in Tables 5-7 shows the results when controlling for the domestic financial conditions index (FCI). Across all three measures, the lag of the FCI has a negative sign and is statistically significant implying, in line with expectations that tighter financial conditions are associated with less risky corporate credit allocation. Importantly, the interaction terms with the growth in credit to GDP ratio remain positive and statistically significant. The results are unchanged when we use the 3-month money market rates or domestic corporate spreads (not shown) instead of the FCI, and when we include global financial variables (VIX index and the federal funds rate) instead of time fixed effects (column 2 in Tables 5-7).

A potential drawback of our approach is that our measures of riskiness of corporate credit allocation do not distinguish between bank versus bond credit, while the majority of the macroprudential policy measures affect bank lending only. There are, however, several channels through which household-specific MaPPs binding for banks only, could affect non-bank corpo-

Table (5) *Robustness: TDTA measure of credit riskiness*

VARIABLES	(1) TDTA	(2) TDTA	(3) TDTA	(4) TDTA	(5) TDTA	(6) TDTA
$TDTA_{t-1}$	0.49*** (0.04)	0.50*** (0.05)	0.47*** (0.05)	0.47*** (0.05)	0.52*** (0.02)	0.48*** (0.04)
$\bar{\varepsilon}_{t-1}^{HH}$	0.02 (0.03)	0.02 (0.03)	0.03 (0.03)	0.04 (0.08)	-0.02 (0.05)	0.02 (0.03)
$\bar{\varepsilon}_{t-1}^{BC}$	0.02 (0.05)	-0.01 (0.04)	0.00 (0.05)	-0.04 (0.10)	0.01 (0.04)	0.03 (0.05)
$\bar{\varepsilon}_{t-1}^{HH} \times \Delta Credit_{t-1}$	0.01* (0.01)	0.01* (0.01)	0.01** (0.01)	0.01 (0.01)	0.02*** (0.01)	0.01* (0.01)
$\bar{\varepsilon}_{t-1}^{BC} \times \Delta Credit_{t-1}$	-0.02* (0.01)	-0.02 (0.01)	-0.03** (0.01)	-0.02 (0.01)	-0.02* (0.01)	-0.02* (0.01)
$\Delta Credit_{t-1}$	0.01** (0.01)	0.01 (0.01)	0.02** (0.01)	0.01* (0.01)	0.01* (0.00)	0.01** (0.01)
ΔGDP_{t-1}	0.03** (0.01)	0.04*** (0.01)	0.04*** (0.01)	0.04*** (0.01)	0.03** (0.01)	0.03** (0.01)
$\Delta_q ER_{t-1}$	-0.02** (0.01)	-0.02** (0.01)	-0.02** (0.01)	-0.02*** (0.01)	-0.02** (0.01)	-0.02*** (0.01)
FCI_{t-1}	-0.13** (0.05)	-0.15*** (0.04)	-0.07 (0.05)	-0.07 (0.05)	-0.14** (0.06)	-0.12* (0.06)
Global Volatility		0.10*** (0.03)				
Fed Funds Rate (Difference)		-0.00 (0.04)				
$\Delta NFCBonds_{t-1}$			-0.03 (0.05)			
$\bar{\varepsilon}_{t-1}^{HH} \times \Delta NFCBonds_{t-1}$			-0.16 (0.09)			
$\bar{\varepsilon}_{t-1}^{BC} \times \Delta NFCBonds_{t-1}$			0.53 (0.37)			
Bond_credit_ratio_ma				-0.01 (0.00)		
$\bar{\varepsilon}_{t-1}^{HH} \times Bond_credit_ratio_ma$				-0.00 (0.00)		
$\bar{\varepsilon}_{t-1}^{BC} \times Bond_credit_ratio_ma$				0.01 (0.01)		
ΔHPI_{t-1}						0.00 (0.00)
Observations	1,108	1,108	1,026	1,013	924	1,108
Number of Nat_Code	21	21	21	20	18	21
Adjusted R-squared	0.40	0.37	0.39	0.39	0.42	0.40
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Additional variables - “Global Volatility” stands for MSCI World Index, “Fed funds rate (Difference)” is the quarterly change in FFR/ Wu-Xia shadow rate, FCI is the domestic financial conditions index, $\Delta NFCBonds$ is yoy growth in outstanding bonds to the nonfinancial corporate sector relative to GDP, “Bond_credit_ratio_ma” is a 4-quarter moving average of the ratio of outstanding NFC bonds to outstanding NFC bank loans, ΔHPI is yoy real house price growth.

Table (6) *Robustness: TDtE measure of credit riskiness*

VARIABLES	(1) TDtE	(2) TDtE	(3) TDtE	(4) TDtE	(5) TDtE	(6) TDtE
$TDtE_{t-1}$	0.36*** (0.03)	0.37*** (0.04)	0.36*** (0.04)	0.35*** (0.04)	0.37*** (0.03)	0.36*** (0.03)
$\bar{\varepsilon}_{t-1}^{HH}$	-0.09** (0.04)	-0.07* (0.04)	-0.09** (0.04)	0.00 (0.08)	-0.05 (0.06)	-0.09** (0.04)
$\bar{\varepsilon}_{t-1}^{BC}$	0.02 (0.08)	0.05 (0.09)	-0.03 (0.10)	-0.05 (0.10)	0.01 (0.08)	0.02 (0.08)
$\bar{\varepsilon}_{t-1}^{HH} \times \Delta Credit_{t-1}$	0.02*** (0.01)	0.02** (0.01)	0.02*** (0.01)	0.02** (0.01)	0.02** (0.01)	0.02*** (0.01)
$\bar{\varepsilon}_{t-1}^{BC} \times \Delta Credit_{t-1}$	-0.01 (0.01)	-0.02 (0.01)	-0.04** (0.02)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)
$\Delta Credit_{t-1}$	0.02** (0.01)	0.02*** (0.01)	0.02** (0.01)	0.02* (0.01)	0.02** (0.01)	0.02** (0.01)
ΔGDP_{t-1}	0.05** (0.02)	0.04*** (0.02)	0.05*** (0.02)	0.05** (0.02)	0.04** (0.02)	0.05*** (0.02)
$\Delta_q ER_{t-1}$	0.00 (0.01)	0.01 (0.01)	0.00 (0.01)	-0.00 (0.01)	0.00 (0.01)	0.00 (0.01)
FCI_{t-1}	-0.21** (0.08)	-0.17** (0.07)	-0.16* (0.09)	-0.16 (0.10)	-0.22** (0.09)	-0.21** (0.09)
Global Volatility		0.07* (0.03)				
Fed Funds Rate (Difference)		-0.02 (0.06)				
$\Delta NFCBonds_{t-1}$			0.00 (0.03)			
$\bar{\varepsilon}_{t-1}^{HH} \times \Delta NFCBonds_{t-1}$			-0.08 (0.08)			
$\bar{\varepsilon}_{t-1}^{BC} \times \Delta NFCBonds_{t-1}$			1.15** (0.55)			
Bond_credit_ratio_ma				-0.01 (0.01)		
$\bar{\varepsilon}_{t-1}^{HH} \times Bond_credit_ratio_ma$				-0.00 (0.00)		
$\bar{\varepsilon}_{t-1}^{BC} \times Bond_credit_ratio_ma$				0.01 (0.01)		
ΔHPI_{t-1}						0.00 (0.01)
Observations	1,098	1,098	1,017	1,003	921	1,098
Number of Nat_Code	21	21	21	20	18	21
Adjusted R-squared	0.26	0.26	0.26	0.26	0.28	0.26
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Additional variables - “Global Volatility” stands for MSCI World Index, “Fed funds rate (Difference)” is the quarterly change in FFR/ Wu-Xia shadow rate, FCI is the domestic financial conditions index, $\Delta NFCBonds$ is yoy growth in outstanding bonds to the nonfinancial corporate sector relative to GDP, “Bond_credit_ratio_ma” is a 4-quarter moving average of the ratio of outstanding NFC bonds to outstanding NFC bank loans, ΔHPI is yoy real house price growth.

Table (7) *Robustness: ICR measure of credit riskiness*

VARIABLES	(1) ICR	(2) ICR	(3) ICR	(4) ICR	(5) ICR	(6) ICR
ICR_{t-1}	0.32*** (0.04)	0.33*** (0.04)	0.31*** (0.05)	0.30*** (0.04)	0.33*** (0.04)	0.32*** (0.04)
$\bar{\varepsilon}_{t-1}^{HH}$	-0.05 (0.04)	-0.03 (0.03)	-0.05 (0.04)	0.06 (0.09)	-0.04 (0.07)	-0.05 (0.04)
$\bar{\varepsilon}_{t-1}^{BC}$	0.01 (0.07)	0.03 (0.06)	-0.02 (0.08)	-0.10 (0.09)	0.01 (0.07)	0.01 (0.07)
$\bar{\varepsilon}_{t-1}^{HH} \times \Delta Credit_{t-1}$	0.02* (0.01)	0.01* (0.01)	0.02* (0.01)	0.01 (0.01)	0.02* (0.01)	0.02* (0.01)
$\bar{\varepsilon}_{t-1}^{BC} \times \Delta Credit_{t-1}$	-0.02 (0.02)	-0.03 (0.02)	-0.04** (0.02)	-0.02 (0.02)	-0.02 (0.02)	-0.02 (0.02)
$\Delta Credit_{t-1}$	0.01 (0.01)	0.02* (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01* (0.01)
ΔGDP_{t-1}	0.02 (0.02)	0.02 (0.02)	0.03 (0.02)	0.02 (0.02)	0.01 (0.02)	0.02 (0.01)
$\Delta_q ER_{t-1}$	0.00 (0.01)	0.01 (0.01)	0.00 (0.01)	0.00 (0.01)	0.01 (0.01)	0.00 (0.01)
FCI_{t-1}	-0.20** (0.08)	-0.17** (0.06)	-0.15* (0.08)	-0.15* (0.09)	-0.21** (0.09)	-0.21** (0.09)
Global Volatility		0.11*** (0.04)				
Fed Funds Rate (Difference)		-0.04 (0.06)				
$\Delta NFCBonds_{t-1}$			0.00 (0.03)			
$\bar{\varepsilon}_{t-1}^{HH} \times \Delta NFCBonds_{t-1}$			-0.11 (0.11)			
$\bar{\varepsilon}_{t-1}^{BC} \times \Delta NFCBonds_{t-1}$			0.99* (0.48)			
Bond_credit_ratio_ma				-0.01 (0.00)		
$\bar{\varepsilon}_{t-1}^{HH} \times Bond_credit_ratio_ma$				-0.00 (0.00)		
$\bar{\varepsilon}_{t-1}^{BC} \times Bond_credit_ratio_ma$				0.01 (0.01)		
ΔHPI_{t-1}						-0.00 (0.01)
Observations	1,108	1,108	1,026	1,013	924	1,108
Number of Nat_Code	21	21	21	20	18	21
Adjusted R-squared	0.19	0.20	0.19	0.19	0.20	0.19
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Additional variables - “Global Volatility” stands for MSCI World Index, “Fed funds rate (Difference)” is the quarterly change in FFR/ Wu-Xia shadow rate, FCI is the domestic financial conditions index, $\Delta NFCBonds$ is yoy growth in outstanding bonds to the nonfinancial corporate sector relative to GDP, “Bond_credit_ratio_ma” is a 4-quarter moving average of the ratio of outstanding NFC bonds to outstanding NFC bank loans, ΔHPI is yoy real house price growth.

rate credit. For example, as discussed in Bengui and Bianchi (2019), a perception of reduced risks in the economy as a result of macroprudential action in the household sector could induce agents in other sectors to take on more risk. Additionally, in response to limited lending opportunities in the retail segment, banks could begin to compete more aggressively in the market for corporate credit, contributing to lowering of credit standards for corporate bonds as well. Nevertheless, one could expect the impact of macroprudential measures, including any leakages from household-specific measures, on corporate credit riskiness to be smaller in countries where the corporate sector relies more on bond funding relative to bank lending. To test this hypothesis, we extend our baseline regression by including either i) lagged year-on-year growth of quarterly corporate bond issuance (column 3 in Tables 5-7) or ii) a four-quarter moving average of the ratio of outstanding corporate bonds to outstanding corporate bank credit (column 4 in Tables 5-7), and their interactions with the macroprudential policy variables.

For all measures of riskiness, the result that an unexpected tightening of household-specific macroprudential measures increases corporate credit riskiness is robust to including the growth of corporate bond issuance. The interaction terms of $\bar{\varepsilon}^{HH}$ with corporate bond issuance, while negative in line with our hypothesis, are not statistically significant. At the same time, the interaction terms of $\bar{\varepsilon}^{BC}$ with credit to GDP growth are now statistically significant and negative, while the interaction terms of $\bar{\varepsilon}^{BC}$ with corporate bond issuance are significant and positive. Thus, the impact of tightening of corporate and broad-based MaPP measures on reducing corporate credit riskiness is declining with the volume of recent corporate bond issuance.

When including the ratio of corporate bonds to corporate bank credit, the interaction term between the $\bar{\varepsilon}^{HH}$ and credit to GDP growth, while positive across the three measures of corporate credit riskiness, is only significant for the TDtE measure. At the same time, the interaction of $\bar{\varepsilon}^{HH}$ with the bonds-to-bank credit ratio, while again negative, is never statistically significant.

We also check whether our results are not due to individual countries. In column 5 in Tables 5-7 we exclude three countries (Canada, Netherlands, and South Korea) that predominantly used household-specific MaPPs and had very few or no instances of the corporate-specific or broad-based macroprudential policy changes. The results are robust to exclusion of the outliers.

It is also possible that our results are driven purely by the positive correlation between the corporate credit riskiness and the situation in the domestic household credit markets. In this case, a tightening in household-specific MaPPs in response to vulnerabilities building up for example in the housing market (as reflected e.g. in the rapid house price growth) could spuriously show up as amplifying risks in the corporate sector as well. To exclude that possibility, besides using macroprudential policy *shocks*, in column 6 of Tables 5-7 we also control for a lag of year-on-year growth in real house prices. The results remain statistically significant. As an additional test, we compute the correlation between year-on-year real house price growth and the three measures of corporate credit riskiness. The cross-country average of that correlation

is low, and ranges between 0.08 and 0.14 for the three measures. Yet, since there is considerable variation between countries, we rerun regressions when excluding five countries for which the correlation between house price growth and corporate riskiness exceeded 0.4 on average (Brazil, Finland, Italy, Poland and Spain). The results (not shown) remain unchanged.

Additional robustness exercises. Finally, in Appendix A.3 we show, for completeness, that the household-specific MaPPs are effective in accomplishing their primary goals: a household-specific MaPP shock slows down growth of credit to the household sector as well as house price growth. In Appendices A.4 and A.5 we show that the results carry through when using local projections akin to Jordá (2005), and when using macroprudential policy actions instead of policy shocks. We also check that the results are robust to using Discroll-Kraay standard errors to control for potential cross-section correlation of standard errors. However, since this way of computing standard errors involves imposing restrictions on the autocorrelation process, and because autocorrelation seems to be of more concern in our dynamic specification than cross-section correlation, we use robust standard errors throughout the paper.¹⁰

Alternative definitions of MaPP measures. To further validate our results, we replace our MaPP shocks with shocks constructed using the alternate indicators of $MaPP^{HH}$ and $MaPP^{BC}$, as explained in Section 3. Table 8 show the results. Columns 1-3 consider a specification where the household-specific MaPP shocks are constructed using the alternate $MaPP^{HH}$ indicator. We see that the interaction term of $\varepsilon^{HH,Alternate}$ with the credit to GDP growth is always positive although ceases to be statistically significant for the TDTA riskiness measure.¹¹

Similarly, columns 4-6 in Table 8 show the results when using the alternate definition of $MaPP^{BC}$ to construct broad-based and corporate sector-specific MaPP shocks. The interaction term of the baseline household-specific MaPP shock with credit to GDP growth is always positive and statistically significant for all three measures of corporate credit riskiness.

¹⁰In all regressions we include time fixed effects, which should mitigate the cross-section correlation concerns.

¹¹This result suggests that restrictions on loan characteristics might be relatively less binding than other MaPP measures we consider.

Table (8) *Alternative definitions of MaPP measures*

VARIABLES	(1) TDTA	(2) ICR	(3) TDtE	(4) TDTA	(5) ICR	(6) TDtE
$DependentVariable_{t-1}$	0.489*** (0.043)	0.326*** (0.040)	0.381*** (0.037)	0.485*** (0.042)	0.326*** (0.040)	0.381*** (0.037)
$\bar{\varepsilon}_{t-1}^{HH,Alternate}$	0.023 (0.025)	-0.019 (0.029)	-0.047 (0.039)			
$\bar{\varepsilon}_{t-1}^{HH,Alternate} \times \Delta Credit_{t-1}$	0.008 (0.006)	0.009* (0.005)	0.014** (0.005)			
$\bar{\varepsilon}_{t-1}^{BC}$	0.021 (0.043)	0.021 (0.065)	0.030 (0.077)			
$\bar{\varepsilon}_{t-1}^{BC} \times \Delta Credit_{t-1}$	-0.018 (0.012)	-0.022 (0.019)	-0.014 (0.014)			
$\Delta Credit_{t-1}$	0.018*** (0.006)	0.022** (0.009)	0.028*** (0.008)	0.020*** (0.005)	0.023** (0.009)	0.029*** (0.008)
ΔGDP_{t-1}	0.040*** (0.011)	0.030** (0.012)	0.054*** (0.015)	0.043*** (0.010)	0.034*** (0.012)	0.056*** (0.015)
$\Delta_q ER_{t-1}$	-0.010* (0.005)	0.013** (0.006)	0.010 (0.006)	-0.011* (0.005)	0.012* (0.006)	0.009 (0.006)
$\bar{\varepsilon}_{t-1}^{HH}$				0.018 (0.025)	-0.031 (0.031)	-0.070* (0.038)
$\bar{\varepsilon}_{t-1}^{HH} \times \Delta Credit_{t-1}$				0.013** (0.005)	0.013* (0.007)	0.022** (0.009)
$\bar{\varepsilon}_{t-1}^{BC,Alternate}$				0.014 (0.107)	0.024 (0.082)	0.040 (0.111)
$\bar{\varepsilon}_{t-1}^{BC,Alternate} \times \Delta Credit_{t-1}$				-0.025 (0.015)	-0.015 (0.025)	-0.022 (0.026)
Observations	1,257	1,257	1,247	1,257	1,257	1,247
Number of Nat_Code	24	24	24	24	24	24
Adjusted R-squared	0.380	0.172	0.253	0.380	0.171	0.254
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Alternate HH measure	Yes	Yes	Yes			
Alternate BC measure				Yes	Yes	Yes

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Note: $\bar{\varepsilon}_{t-1}^{HH(BC),Alternate}$ is the lagged sum of alternative measure of $MaPP^{HH(BC)}$ shock in past four quarters, $\bar{\varepsilon}_{t-1}^{HH(BC)}$ is the lagged sum of the baseline $MaPP^{HH(BC)}$ shocks in past four quarter, $\Delta Credit_{t-1}$ is the lagged yoy growth of credit to non-financial private sector relative to GDP, ΔGDP_{t-1} is the lagged yoy Real GDP growth, $\Delta_q ER_{t-1}$ is the lagged qoq local currency appreciation rate against USD.

5.3 Lending standards from loan officer surveys

As a final robustness exercise, and to extend our analysis, we collect data on changes in the lending standards for corporate loans as reported by bank loan officers in surveys. As the loan officer surveys provide information on loan lending standards by the firm size, we can study the impact of MaPP actions on bank loans to SMEs and large corporates separately. Columns 1, 3 and 5 in Table 9 show the results from the baseline regression (1) for all corporations, SMEs and to large corporates respectively.¹² Columns 2, 4 and 6 in Table 9 further control for domestic conditions using the local 3-month money market rates.¹³ When interpreting the results, it is important to remember that positive values of the lending standards variable mean tightened standards, and negative values - eased lending standards.

Across all specifications, the joint significance tests of the four lags of the household-specific macroprudential shocks show they are statistically significant, but the direction of the impact varies by the firm size. In particular, regressions for lending standards for all corporates and for SMEs show a positive (i.e. tightening) impact of past unexpected MaPP tightenings on the lending standards by banks. However, the opposite is true for large corporates, where the net impact of MaPP tightening shocks in the past four quarters is negative, suggesting an easing of lending conditions by banks.

These findings are consistent with the evidence that the owners of small firms oftentimes use personal real estate as collateral for firm loans (Adelino, Schoar and Severino (2016), Bahaj et al. (2019)). In particular, Lian and Ma (2020) show, for the U.S., that asset-based (collateralized) loans are more common among small and young firms, compared to large and old corporates who rely more on cash flow-based loans. In the macroprudential policy context, Ayyagari, Beck and Martinez-Peria (2018) show varying effects of borrower-based tools on mitigating *credit growth* by firm size. Finally, the results based on loan officer surveys are also consistent with the results for riskiness of corporate allocation measures, which we constructed using data for listed companies. Overall, the evidence gathered in this paper suggests that the leakages from household-specific MaPPs are likely more pronounced for credit to the large corporates.

¹²We also ran the regression (2) but since only the standalone terms of the macroprudential policy shocks were statistically significant, we decided to use the baseline specification without interaction with credit growth.

¹³We use the 3-month market rates instead of domestic FCI to maximize the number of countries in the sample.

Table (9) *Bank Lending Standards for Corporate Loans*

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	LS(All)	LS(All)	LS(SMEs)	LS(SMEs)	LS(Large)	LS(Large)
<i>DependentVariable</i> _{<i>t</i>-1}	0.716***	0.716***	0.680***	0.681***	0.680***	0.675***
	(0.068)	(0.070)	(0.079)	(0.082)	(0.080)	(0.086)
ε^{HH} , Lag 1	1.301**	1.302**	1.897*	1.892*	0.043	0.076
	(0.576)	(0.591)	(1.034)	(1.045)	(0.743)	(0.745)
ε^{HH} , Lag 2	-1.216	-1.216	-1.351	-1.352	-0.991	-0.990
	(0.744)	(0.744)	(0.880)	(0.880)	(0.872)	(0.876)
ε^{HH} , Lag 3	-0.503	-0.503	0.687	0.687	-1.616*	-1.615*
	(0.737)	(0.741)	(1.010)	(1.011)	(0.869)	(0.863)
ε^{HH} , Lag 4	-1.440	-1.440	-0.037	-0.041	-0.783	-0.774
	(0.916)	(0.915)	(0.934)	(0.929)	(0.815)	(0.830)
ε^{BC} , Lag 1	-1.140	-1.140	-2.258	-2.263	-2.051*	-2.010*
	(0.900)	(0.979)	(1.758)	(1.770)	(1.025)	(1.125)
ε^{BC} , Lag 2	-1.731	-1.730	-0.036	-0.041	-2.483	-2.448
	(1.348)	(1.352)	(1.425)	(1.430)	(1.881)	(1.895)
ε^{BC} , Lag 3	-0.680	-0.679	0.616	0.597	0.570	0.682
	(1.944)	(1.805)	(1.261)	(1.220)	(2.174)	(1.985)
ε^{BC} , Lag 4	-1.605	-1.604	-2.569*	-2.589*	-0.382	-0.261
	(1.498)	(1.660)	(1.297)	(1.447)	(1.930)	(2.087)
$\Delta Credit$ _{<i>t</i>-1}	0.177*	0.177*	0.251**	0.254**	0.157	0.139
	(0.095)	(0.100)	(0.108)	(0.112)	(0.128)	(0.137)
ΔGDP _{<i>t</i>-1}	0.344*	0.344**	0.310	0.302	0.365	0.414
	(0.193)	(0.151)	(0.242)	(0.185)	(0.252)	(0.255)
$\Delta_q ER$ _{<i>t</i>-1}	0.166	0.166	0.079	0.076	0.002	0.023
	(0.132)	(0.117)	(0.148)	(0.132)	(0.123)	(0.115)
<i>NR</i> _{<i>t</i>-1}		0.003		-0.053		0.335
		(0.539)		(0.560)		(0.583)
Observations	743	743	644	644	644	644
Number of Countries	15	15	13	13	13	13
Adjusted R-squared	0.660	0.659	0.587	0.586	0.622	0.622
Domestic 3-m rate	No	Yes	No	Yes	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
p-value (Joint F-test for 4 lags ε^{HH})	0.06	0.06	0.08	0.08	0.03	0.03
p-value (Joint F-test for 4 lags ε^{BC})	0.28	0.39	0.32	0.37	0.16	0.19

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Additional variables - NR is the 3-month nominal domestic market interest rate.

6 Conclusions

We contribute to the literature on spillovers and leakages from financial regulations by providing evidence of leakages from household sector-specific macroprudential regulations to corporate borrowers. We construct three country-level measures of the riskiness of corporate credit allocation for a range of advanced and emerging economies, using firm-level data. Consistently across the three measures, we find that a tightening of household-specific macroprudential tools increases the riskiness of corporate credit allocation and that this effect is more pronounced during credit expansion cycles. The effects are economically meaningful: an unexpected tightening in the household-specific restrictions increases the credit riskiness measure by an average of 10 percent when the credit to GDP ratio grows at a rate one standard deviation above its mean. When replacing our measures of riskiness of corporate credit allocation with the changes in bank lending standards reported in loan officer surveys, the results indicate that the leakages from household-specific macroprudential policy actions might be particularly pronounced for large corporates, while actually tightening lending standards for SMEs.

Overall, our paper provides evidence that the cross-sectoral leakages from macroprudential policies might be quantitatively important. Thus, such effects should be taken into account by the policymakers deciding between broad-based and sector-specific macroprudential policy tools. In particular, our results support early policy interventions, i.e. during the early phase of the credit cycle, when sectoral leakages are likely to be still low.

REFERENCES

- Acharya, Viral, Tim Eisert, Christian Eufinger and Christian W. Hirsch (2016), ‘Whatever it takes: The real effects of unconventional monetary policy’, *SAFE Working Paper 152* .
- Acharya, Viral V., Katharina Bergant, Matteo Crosignani, Tim Eisert and Fergal McCann (2020), ‘The anatomy of the transmission of macroprudential policies’, *IMF Working Paper 20/58* .
- Adelino, Manuel, Antoinette Schoar and Felipe Severino (2016), ‘Loan Originations and Defaults in the Mortgage Crisis: The Role of the Middle Class’, *The Review of Financial Studies* **29**(7), 1635–1670.
- Ahnert, Toni, Kristin Forbes, Christian Friedrich and Dennis Reinhardt (2020), ‘Macroprudential fx regulations: Shifting the snowbanks of fx vulnerability?’, *Journal of Financial Economics*, *forthcoming* .
- Aiyar, Shekhar, Charles W. Calomiris and Tomasz Wieladek (2014), ‘Does macro-prudential regulation leak? evidence from a uk policy experiment’, *Journal of Money, Credit and Banking* **46**(s1), 181–214.

- Akinci, Ozge and Jane Olmstead-Rumsey (2018), ‘How effective are macroprudential policies? an empirical investigation’, *Journal of Financial Intermediation* **33**, 33 – 57.
- Alam, Zohair, Adrian Alter, Jesse Eiseman, Gaston Gelos, Heedon Kang, Machiko Narita, Erlend Nier and Naixi Wang (2019), ‘Digging deeperevidence on the effects of macroprudential policies from a new database’, *IMF Working Paper No. 19/66* .
- Araujo, Juliana D., Manasa Patnam, Adina Popescu, Fabian Valencia and Weijia Yao (2020), ‘Effects of macroprudential policy: Evidence from over 6,000 estimates’, *IMF Working Paper No. 20/67* .
- Auer, Raphael and Steven Ongena (2016), ‘The countercyclical capital buffer and the composition of bank lending’, *BIS Working Paper No. 593* .
- Ayyagari, Meghana, Thorsten Beck and Maria Soledad Martinez-Peria (2018), ‘The micro impact of macroprudential policies: Firm-level evidence’, *IMF Working Paper 18/267* .
- Bahaj, Saleem, Angus Foulis, Gabor Pinter and Paolo Surico (2019), ‘Employment and the collateral channel of monetary policy’, *Bank of England working papers 827* .
- Bengui, Julien and Javier Bianchi (2018), ‘Macroprudential policy with leakages’, *Federal Reserve Bank of Minneapolis Working Paper 754* .
- Brandão Marques, Luis, Gaston Gelos, Machiko Narita and Erlend Nier (2020), ‘Leaning against the wind: A cost-benefit analysis for an integrated policy framework’, *IMF Working Paper No. 20/123* .
- Brandão Marques, Luis, Qianying Chen, Claudio Raddatz, Jérôme Vandenbussche and Peichu Xie (2019), ‘The riskiness of credit allocation and financial stability’, *IMF Working Paper No. 19/207* .
- Cerutti, Eugenio, Stijn Claessens and Luc Laeven (2017), ‘The use and effectiveness of macroprudential policies: New evidence’, *Journal of Financial Stability* **28**, 203–224.
- Danisewicz, Piotr, Dennis Reinhardt and Rhiannon Sowerbutts (2017), ‘On a tight leash: Does bank organizational structure matter for macroprudential spillovers?’, *Journal of International Economics* **109**, 174 – 194.
- Forbes, Kristin and Michael Klein (2015), ‘Pick Your Poison: The Choices and Consequences of Policy Responses to Crises’, *IMF Economic Review* **63**, 197–237.
- Gelos, Gaston and Alejandro Werner (2002), ‘Credit booms and macrofinancial stability’, *Journal of Development Economics* **67**(1), 1–27.

- Greenwood, Robin and Samuel G. Hanson (2013), ‘Issuer Quality and Corporate Bond Returns’, *The Review of Financial Studies* **26**(6), 1483–1525.
- Houston, Joel F., Chen Lin and Yue Ma (2012), ‘Regulatory arbitrage and international bank flows’, *The Journal of Finance* **67**(5), 1845–1895.
- International Monetary Fund (2017), ‘Are countries losing control of domestic financial conditions?’, *Global Financial Stability Report: Chapter 3* (April).
- International Monetary Fund (2018), ‘The riskiness of credit allocation: A source of financial vulnerability?’, *Global Financial Stability Report: Chapter 2* (April).
- Jordá, Óscar (2005), ‘Estimation and inference of impulse responses by local projections’, *American Economic Review* **95**(1), 161–182.
- Kirti, Divya (2020), ‘Lending standards and output growth (july, 2018)’, *ESRB: Working Paper Series No. 2018/79* .
- Koop, Gary and Dimitris Korobilis (2014), ‘A new index of financial conditions’, *European Economic Review* **71**, 101–116.
- Kuttner, Kenneth N. and Ilhyock Shim (2016), ‘Can non-interest rate policies stabilize housing markets? evidence from a panel of 57 economies’, *Journal of Financial Stability* **26**, 31–44.
- Lian, Chen and Yueran Ma (2020), ‘Anatomy of corporate borrowing constraints’, *Quarterly Journal of Economics*, *forthcoming* .
- Ongena, Steven, Alexander Popov and Gregory F. Udell (2013), ‘when the cat’s away the mice will play: Does regulation at home affect bank risk-taking abroad?’, *Journal of Financial Economics* **108**(3), 727 – 750.
- Temesvary, Judit (2018), ‘The role of regulatory arbitrage in u.s. banks’ international flows: Bank-level evidence’, *Economic Inquiry* **56**(4), 2077–2098.
- Wu, Jing Cynthia and Fan Dora Xia (2016), ‘Measuring the macroeconomic impact of monetary policy at the zero lower bound’, *Journal of Money, Credit and Banking* **48**(2-3), 253–291.

A Appendix

A.1 Data: sources and definitions

Table (A1) *Variables and data sources.*

Variable	Description	Source
total assets, total debt, EBITDA, Debt Interest Expense	balance sheet variables needed to compute the measures of corporate credit riskiness	Datastream
3-month money market rate	measure of domestic fin. conditions	Datastream
MSCI VIX, U.S. policy rates	measures of global financial conditions	Datastream
global shadow rate	shadow US policy rate	Wu and Xia (2016)
macroprudential policy indices	$MaPP^{HH}$: a sum of indicators LTV , $DSTI$, $LoanR^{HH}$; $MaPP^{BC}$: a sum of indicators $Capital^{Gen}$, $Capital^{Corp}$ Conservation, CCB , LCG^{Gen} , LCG^{Corp} , $LoanR$, $LoanR^{Corp}$	iMaPP database, Alam et al. (2019)
real GDP	growth rates	WEO database
exchange rate against USD		
real house price index	growth rate	IMF
Financial Conditions Index (FCI)	index based on: corporate, interbank, sovereign spreads, term spreads, long-term interest rates, equity return volatility, equity and house price returns, market share of the financial sector, and credit growth	IMF (2017)
credit to domestic nonfinancial private sector, and to domestic NFCs, NFC bonds outstanding	ratios relative to GDP, growth rates	BIS
corporate bond to credit ratio	ratio of NFC bonds outstanding to credit to nonfinancial corporates, four-quarter moving average	BIS
Capital Account Openness	Chin and Ito's Index	IMF AREAER database
average LTV limit	simple average of regulatory LTV limits on all existing loan categories; when a country does not have LTV limits, the value is set at 100	iMaPP database Alam et al. (2019)
bank lending standards from loan officer surveys	measure of a change in lending standards: a positive value indicates a tightening, a negative value—an easing	Haver Analytics

A.2 Construction of macroprudential policy shocks

We proceed in two steps. First, for both MaPP indicators, $MaPP^{HH}$ and $MaPP^{BC}$, we estimate the following ordered probit regression:

$$\tilde{MaPP}_{i,t}^j = \alpha_i + \mu_t + \beta_1 X_{i,t-1} + \beta_2 GDP_{i,t}^f + \epsilon_{i,t}, \quad (\text{A.1})$$

where $\tilde{MaPP}_{i,t}^j$ is a categorical macroprudential indicator, with $j = \{HH, BC\}$, which takes values $\{-2, -1, 0, 1, 2\}$ if, in net terms, there were more than one loosening actions, one loosening

action, no change, one tightening action, or more than two tightening actions in the quarter t in country i , respectively. The vector $X_{i,t-1}$ consists of the following control variables: year-on-year real GDP growth, quarter-on-quarter growth in credit to GDP ratio, financial development index (FDI), Chinn and Ito's capital account openness index, quarter-on-quarter USD bilateral exchange rate change and quarter-on-quarter house price growth. All variables are lagged one quarter, except for the FDI and the capital account openness indices—which are only available at annual frequency and thus we include a fourth lag of the two variables. The variable $GDP_{i,t}^f$ stands for one-year ahead Consensus forecast of real GDP growth.

The policy shock is then recovered as the difference between the actual value of the macroprudential indicator and its estimated conditional expectation:

$$\tilde{\varepsilon}_{i,t}^j = Ma\tilde{P}P_{i,t}^j - \sum_{k=-2}^2 \hat{p}_k(X_{i,t-1}, GDP_{i,t}^f)k, \quad (\text{A.2})$$

where $\hat{p}_k(X_{i,t-1}, GDP_{i,t}^f)$ is the estimated probability of $Ma\tilde{P}P_{i,t}^j = k$, with $k \in \{-2, -1, 0, 1, 2\}$ conditional on the right-hand side variables of equation (A.1).

The first two columns of the Table A2 present results for the specification (A.1). The last two columns show an alternative specification, in which growth of the credit to GDP ratio is replaced by bank credit growth in the regression for the $Ma\tilde{P}P^{HH}$, and by bank credit growth and growth in nonfinancial corporates bonds-to-GDP ratio in the regression for the $Ma\tilde{P}P^{BC}$. Additionally, in the regression for the $Ma\tilde{P}P^{HH}$, we add a domestic financial conditions index, and in the regressions for $Ma\tilde{P}P^{BC}$ —the 3-month money market rate (the results for $Ma\tilde{P}P^{BC}$ are unchanged when including the FCI instead of the short-term rate albeit the number of observations declines further in that case). Given the reduced number of observations when controlling for bank NFC bond issuance, we choose (A.1) as our preferred specification, but the results remain unchanged when using MaPP shocks derived using specifications in columns (3)-(4), as shown in Table A3.

Table (A2) *Macroprudential shocks: first-stage regressions*

VARIABLES	(1) $M\tilde{a}PP^{BC}$	(2) $M\tilde{a}PP^{HH}$	(3) $M\tilde{a}PP^{BC}$	(4) $M\tilde{a}PP^{HH}$
GDP^f	0.142* (0.085)	0.156** (0.064)	0.250* (0.144)	0.082 (0.090)
ΔGDP_{t-1}	-2.434 (2.899)	-0.504 (2.086)	-1.763 (4.756)	-2.909 (2.581)
$\Delta_q Credit_{t-1}$	-1.572 (2.212)	1.137 (1.678)		
$\Delta_q ER_{t-1}$	-1.407 (1.908)	-1.775 (1.393)	-2.864 (2.576)	-1.216 (1.673)
$CAOpen_{t-1}$	0.139 (0.170)	0.022 (0.112)	0.142 (0.261)	0.088 (0.145)
FDI_{t-1}	-0.581 (1.622)	-2.397** (1.104)	-0.054 (2.187)	-4.183*** (1.486)
$\Delta_q HPI_{t-1}$	1.382 (2.376)	0.994 (1.802)	-0.306 (3.551)	1.596 (2.268)
$\Delta_q BankCredit_{t-1}$			5.010* (2.571)	0.635 (1.633)
$\Delta_q NFCBonds_{t-1}$			-0.197 (0.399)	
$nominalrate_{t-1}$			-0.032 (0.064)	
FCI_{t-1}				-0.353*** (0.132)
Observations	2,861	2,861	1,718	1,914
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Note: Additional variables - GDP^f is the one-year ahead GDP forecasts from Consensus Forecasts, $CAOpen$ is the Chinn Ito's Capital Account Index, FDI is the financial development index, $\Delta_q HPI$ is the qoq real house price growth, $\Delta_q BankCredit$ is qoq growth of real bank credit to the domestic private nonfinancial sector, $\Delta_q NFCBonds$ is the qoq growth of the non-financial corporate bonds to GDP ratio, $nominalrate$ stands for the 3-month money market rate.

Table (A3) *Baseline results with macroprudential shocks derived using alternative first-stage regression specification*

VARIABLES	(1) TDTA	(2) ICR	(3) TDtE
dependent variable, $t - 1$	0.471*** (0.052)	0.313*** (0.052)	0.358*** (0.043)
$\bar{\varepsilon}_{t-1}^{HH}$	-0.002 (0.043)	-0.091* (0.046)	-0.118** (0.054)
$\bar{\varepsilon}_{t-1}^{BC}$	0.011 (0.061)	0.038 (0.065)	0.042 (0.088)
$\bar{\varepsilon}_{t-1}^{HH} \times \Delta Credit_{t-1}$	0.014* (0.007)	0.018* (0.010)	0.024** (0.010)
$\bar{\varepsilon}_{t-1}^{BC} \times \Delta Credit_{t-1}$	-0.013 (0.010)	-0.023 (0.019)	-0.013 (0.014)
$\Delta Credit_{t-1}$	0.013 (0.009)	0.008 (0.011)	0.019* (0.011)
ΔGDP_{t-1}	0.053*** (0.013)	0.032** (0.015)	0.062*** (0.019)
$\Delta_q ER_{t-1}$	-0.018** (0.006)	0.002 (0.006)	-0.001 (0.007)
Observations	849	849	841
Number of Nat.Code	18	18	18
Adjusted R-squared	0.378	0.191	0.249
Country FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Interaction	Yes	Yes	Yes

Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note: Refer to Table 4 for variable descriptions. The macroprudential shocks are derived as residuals from regressions in columns (3)-(4) of the Table A2.

A.3 Macroprudential policies, household lending and house price growth

For completeness, we also show that household-specific macroprudential policies are effective in achieving their frequent operational targets i.e. affecting growth of credit to the household sector and growth of house prices. For this purpose we regress 1) quarter-on-quarter growth in the household credit to GDP ratio ($\Delta_q HHCredit$), and 2) quarter-on-quarter real house price growth ($\Delta_q HPI$) on household-specific macroprudential policy shocks and their interaction with the lagged household credit to GDP growth, while controlling for real GDP growth, exchange rate appreciation against USD, past growth in household credit to GDP ratio and domestic 3-month money market rate. Table A4 presents the results. It shows that an unexpected household-specific MaPP tightening in the past four quarters reduces house price growth and growth of credit to the household sector, and more so when credit growth has been rapid in the recent past.

Table (A4) *Impact of household-specific macroprudential policies on lending to households and house price growth*

VARIABLES	(1) HPI	(2) HPI	(3) HH Credit	(4) HH Credit
$\bar{\varepsilon}_{t-1}^{HH}$	0.057 (0.064)	0.049 (0.062)	0.071 (0.046)	0.067 (0.052)
$\bar{\varepsilon}_{t-1}^{HH} \times \Delta HHCredit_{t-1}$	-0.031** (0.013)	-0.031** (0.013)	-0.078*** (0.013)	-0.077*** (0.012)
$nominalrate_{t-1}$		-0.135*** (0.046)		-0.244*** (0.068)
$\Delta_q HPI_{t-1}$	0.318*** (0.065)	0.308*** (0.066)		
$\Delta_q HHCredit_{t-1}$	0.054*** (0.009)	0.050*** (0.009)	0.125*** (0.026)	0.116*** (0.024)
ΔGDP_{t-1}	0.162*** (0.045)	0.135*** (0.046)	0.063 (0.084)	0.009 (0.060)
$\Delta_q ER_{t-1}$	0.045 (0.028)	0.038 (0.024)	0.079*** (0.023)	0.063*** (0.016)
Observations	1,331	1,322	1,331	1,322
Number of Nat_Code	23	23	23	23
Adjusted R-squared	0.275	0.281	0.370	0.391
Dom FCI	No	Yes	No	Yes
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Note: Additional variables- $\Delta_q HHCredit_{t-1}$ is the quarter-on-quarter growth in the household credit to GDP ratio, $\Delta HHCredit_{t-1}$ is the year-on-year growth in the household credit to GDP ratio. $\Delta_q HPI$ is the quarter-on-quarter real house price growth.

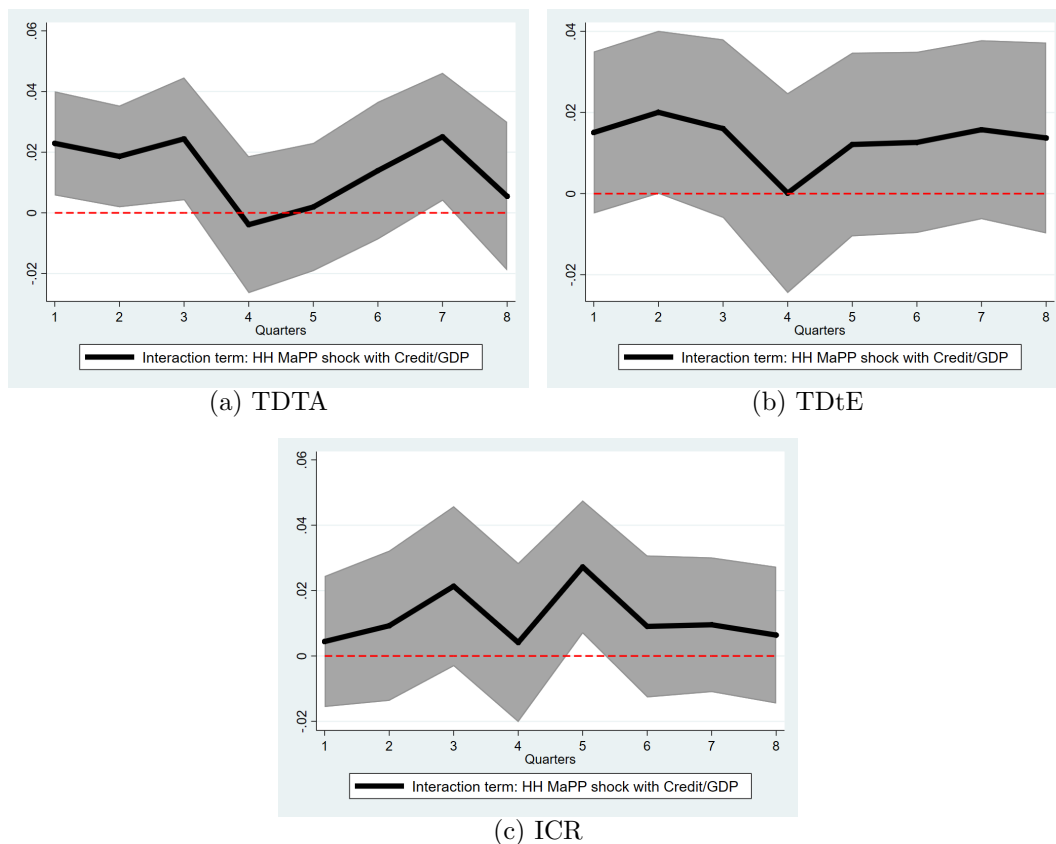
A.4 Deriving impact of macroprudential policies on corporate credit riskiness using local projections

The results are robust to using the local projections in Jordá (2005). To run the local projections, we consider the following regression at horizons $h = 1, 2..8$:

$$\begin{aligned}
 CC_{i,t+h}^s = & \alpha_i^h + \sum_{k=0}^1 \beta_{1,k}^h \varepsilon_{i,t-k}^{HH} + \sum_{k=0}^1 \beta_{2,k}^h \varepsilon_{i,t-k}^{BC} + \beta_3^h \varepsilon_{i,t}^{HH} \times \Delta Credit_{i,t} + \beta_4^h \varepsilon_{i,t}^{BC} \times \Delta Credit_{i,t} + \\
 & + \sum_{k=0}^1 \beta_{5,k}^h \Delta Credit_{i,t-k} + \sum_{k=0}^1 \beta_{6,k}^h \Delta ER_{i,t-k} + \sum_{k=0}^1 \beta_{7,k}^h \Delta GDP_{i,t-k} + \epsilon_{i,t+h}, \quad (A.3)
 \end{aligned}$$

where all variables are defined as in Section 4. Figure 5 shows, for each of the three credit riskiness measures, the coefficients on the interaction term $\varepsilon_{i,t}^{HH} \times \Delta Credit_{i,t}$ at different horizons. For all the three measures, the interaction term is broadly positive and—at some horizons—positive and statistically significant.

Figure (5) *Responses of corporate credit riskiness measures to household-specific macroprudential policy shocks: local projections.*



Note: The figure plots the coefficient β_3^h from equation A.3 for $h = 1, 2, \dots, 8$, for the three measures of the riskiness of corporate credit allocation (TDtA, ICR and TDtE). Grey areas correspond to 90 percent confidence intervals.

A.5 Results with MaPP actions

The results are robust to using macroprudential policy actions rather than shocks. We replace the MaPP shocks in (1) and (2), with changes in policy actions using $MaPP^{HH(BC)}$ and their four-period sums ($MaPP_{sum}^{HH(BC)}$) respectively. Table A5 below present the results for the baseline specifications.

Table (A5) *Baseline results using MaPP actions*

VARIABLES	(1) TDTA	(2) ICR	(3) TDtE	(4) TDTA	(5) ICR	(6) TDtE
$DependentVariable_{t-1}$	0.529*** (0.042)	0.354*** (0.035)	0.406*** (0.035)	0.529*** (0.042)	0.349*** (0.034)	0.402*** (0.035)
$MaPP^{HH}$, Lag 1	0.005 (0.041)	-0.064 (0.043)	-0.078* (0.042)			
$MaPP^{HH}$, Lag 2	0.114** (0.048)	0.004 (0.042)	-0.023 (0.054)			
$MaPP^{HH}$, Lag 3	0.080 (0.047)	0.003 (0.067)	-0.012 (0.058)			
$MaPP^{HH}$, Lag 4	-0.003 (0.043)	0.067* (0.037)	0.056 (0.049)			
$\Delta Credit_{t-1}$	0.022*** (0.005)	0.017*** (0.005)	0.024*** (0.005)	0.022*** (0.005)	0.017*** (0.005)	0.023*** (0.004)
ΔGDP_{t-1}	0.015 (0.018)	0.015 (0.012)	0.032* (0.016)	0.013 (0.018)	0.012 (0.013)	0.029* (0.016)
$\Delta_q ER_{t-1}$	-0.013*** (0.004)	0.010* (0.005)	0.005 (0.005)	-0.013*** (0.004)	0.009* (0.005)	0.004 (0.005)
$MaPP_{sum}^{HH}$				0.042** (0.020)	-0.021 (0.027)	-0.048 (0.034)
$MaPP_{sum}^{BC}$				-0.023 (0.056)	0.009 (0.051)	0.028 (0.052)
$MaPP_{sum}^{HH} \times \Delta Credit_{t-1}$				0.005 (0.005)	0.012** (0.005)	0.014*** (0.005)
$MaPP_{sum}^{BC} \times \Delta Credit_{t-1}$				-0.009 (0.006)	-0.020* (0.010)	-0.016 (0.010)
Observations	1,571	1,571	1,559	1,571	1,571	1,559
Number of Countries	27	27	27	27	27	27
Adjusted R-squared	0.419	0.156	0.235	0.419	0.160	0.237
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Interaction				Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: $MaPP^{HH(BC)}$ is the household-specific (broad-based or corporate-specific) MaPP policy action, $MaPP_{sum}^{HH(BC)}$ is the sum of policy actions in the past four quarters.