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

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Abstract

Sector-specific macroprudential regulations can increase the riskiness of credit to other sectors. First, using cross-country bank-level data we find that after a tightening of household-specific macroprudential policy during a credit expansion, banks with larger portfolios of residential mortgages increase their corporate lending by more than banks with smaller mortgage portfolios. Second, we compute three country-level measures of the riskiness of corporate credit allocation based on firm-level data. Consistently across the measures, an unexpected tightening of household-specific macroprudential tools during a credit expansion is followed by an increase in riskiness of corporate credit. These effects are quantitatively meaningful: the riskiness of corporate credit increases by around 10 percent of the historical standard deviation following an unexpected policy tightening. 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

Keywords: Macroprudential regulations, sector-specific financial regulations, corporate credit risk, corporate loan growth.

Non-technical summary

Macroprudential policies can have indirect effects on the economy that go beyond the direct impact on the lenders or borrowers they target. In this paper we provide evidence on one type of such effects: leakages from sector-specific macroprudential policies (i.e. targeting lending to borrowers in one sector) to borrowers in other sectors. In theory, if lenders have fixed targets for total returns or lending volumes, they could respond to a tightening of regulations in one loan segment by increasing targets in other segments. As a result, credit would flow 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).

From the policy perspective, estimates of such leakage effects could inform the choice between broad-based and targeted macroprudential tools. Yet, empirical evidence so far has been limited to few case studies (e.g. Auer, Matyunina and Ongena 2022, Acharya et al. 2020), making it difficult to generalize conclusions to a broader range of macroprudential policies. Our contribution is to fill this gap by providing evidence on 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) and debt service to income (DSTI) limits, and study their impact on bank corporate lending volumes and on riskiness of corporate credit. First, we demonstrate that as macroprudential regulations become tighter in the household sector, bank lending shifts to the corporates. Using bank-level balance sheet data for a range of countries, we show that after a tightening of household-specific macroprudential measures banks with larger portfolios of residential mortgages (and thus more affected by the policy change) experience higher corporate loan growth compared to banks with smaller mortgage exposures. However, this effect is present during credit expansion booms only, consistent with the past literature showing that macroprudential policies are more effective during periods of rapid credit growth (Araujo et al. 2020).

Second, we show that the risk profile of corporate credit increases too. Using firm-level data for a range of economies, we construct country-level measures of *riskiness of corporate credit allocation* that capture the relative riskiness of firms taking on a lot of new debt (both bank loans and market financing) compared to firms that do not increase their debt financing or increase it by very little. As shown in Greenwood and Hanson (2013), International Monetary Fund (2018) and in Brandão-Marques et al. (2019), measures based on the distribution of new borrowing among firms with different risk profiles predict episodes of financial instability and downside

¹By “leakages” we mean changes in credit to and 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, could be a desirable outcome from the perspective of policymakers.

risks to growth; they also signal a forthcoming crisis better than the underlying conventional corporate vulnerability indicators when considered individually.

Consistently across the measures, we find that a tightening of household-specific macroprudential tools increases the riskiness of corporate credit allocation, but again only during credit expansions. Quantitatively, corporate credit riskiness increases by 10 percent of a historical standard deviation when credit to GDP growth is one standard deviation above its sample mean. Is that a large effect? In the pre-GFC period of 2005-2008, which is known for rapid credit growth and build-up of financial vulnerabilities, the average year-on-year credit to GDP growth across countries stood at 14 percent (over 2.5 standard deviations above the sample mean), while the three riskiness measures increased during the same time by around 80 percent of the standard deviation, on average across countries. Thus, the leakages we document are considerable in magnitude. In fact, for the credit growth of 14 percent in the pre-GFC period, the size of spillovers from an unexpected household-specific macroprudential tightening would be 23 percent of historical standard deviation across the corporate credit riskiness measures.

Overall, our results point to economically meaningful leakages from sector-specific macroprudential tools to other sectors *during credit expansions*. In terms of policy implications, they support policy interventions during the early stages of the credit cycle, when credit vulnerabilities are growing but from low levels and when sectoral leakages are less important. They also point to the importance of timely monitoring of vulnerabilities and riskiness in both household and corporate sectors. In particular, information on the distribution of bank corporate loans by firm size might be relevant for assessing the size of potential leakage effects. While an alternative way to address the leakages this paper identifies would be to design more macroprudential tools targeting firms, this has been challenging in practice due to heterogeneity of business models across firms.

1 Introduction

Macroprudential policies can have indirect effects on the economy that go 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 et al. 2012, Ongena et al. 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 fixed targets for aggregate 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, credit would flow 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 taxes on excessive borrowing, but unregulated agents react to the safer environment by engaging in more risky activities.

From the policy perspective, estimates of such leakage effects could inform the choice between broad-based and targeted macroprudential tools. Yet, empirical evidence so far has been limited to few case studies (e.g. Auer, Matyunina and Ongena 2022, Acharya et al. 2020), making it difficult to generalize conclusions to a broader range of macroprudential policies. Our contribution is to fill this gap by providing evidence on leakages from sector-specific macroprudential tools across a large group of advanced and emerging economies, and by quantifying their magnitude.²

Given their relatively broad adoption, we focus on macroprudential policies targeting borrowing by households, such as loan to income (LTI), loan to value (LTV) and debt service to income (DSTI) limits, and study their impact on bank corporate lending volumes and on riskiness of corporate credit. First, we demonstrate that as macroprudential regulations become tighter in the household sector, bank lending shifts to the corporates. Using bank-level balance sheet data for a range of countries, we show that after an unexpected tightening of household-specific macroprudential measures during a credit expansion, banks with larger portfolios of residential mortgages experience higher corporate loan growth compared to banks with smaller mortgage exposures.

²By “leakages” we mean changes in credit to and 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, could be a desirable outcome from the perspective of policymakers.

Second, we show that the risk profile of corporate credit increases too. Using firm-level data for a range of economies, we construct three country-level measures of *riskiness of corporate credit allocation* that capture the relative riskiness of firms taking on a lot of new debt (both bank loans and market financing) compared to firms that do not increase their debt financing or increase it by very little. As shown in Greenwood and Hanson (2013), International Monetary Fund (2018) and in Brandão-Marques et al. (2019), measures based on the distribution of new borrowing among firms with different risk profiles 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, but only during credit expansions.³ Quantitatively, corporate credit riskiness increases by 10 percent of a historical standard deviation when credit to GDP growth is one standard deviation above its sample mean. Is that a large effect? In the pre-GFC period of 2005-2008, which is known for rapid credit growth and build-up of financial vulnerabilities, the average year-on-year credit to GDP growth across countries stood at 14 percent (over 2.5 standard deviations above the sample mean), while the three riskiness measures increased during the same time by around 80 percent of the standard deviation, on average across countries. Thus, the leakages we document are considerable in magnitude. In fact, for the credit growth of 14 percent in the pre-GFC period, the size of spillovers from an unexpected household-specific macroprudential tightening would be 23 percent of historical standard deviation across the corporate credit riskiness measures.

The results are robust to controlling for domestic and global financial conditions, controlling for housing booms, excluding outliers, applying local projections, using pooled mean group estimation, using different definitions of macroprudential policies, applying alternative specifications for deriving macroprudential policy shocks or looking at 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 of 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 et al. 2016, Bahaj et al. 2019).

Overall, our results point to economically meaningful leakages from sector-specific macroprudential tools to other sectors *during credit expansions*. To provide more intuition for the state-dependence of the leakage effects, we consider a simple model of bank portfolio choice. In

³Since 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.

the model, positive risk sentiment among investors or a positive signal about economic outlook reduce bank funding costs and result in higher bank lending. As bank balance sheets expand, the regulatory capital requirements start to bind, generating interdependence between lending and the risk profile of loans in different loan segments.

In terms of policy implications, our results support policy interventions during the early stages of the credit cycle, when credit vulnerabilities are growing but from low levels and when sectoral leakages are less important. They also point to the importance of timely monitoring of vulnerabilities and riskiness in both household and corporate sectors. In particular, information on the distribution of bank corporate loans by firm size might be relevant for assessing the size of potential leakage effects. While an alternative way to address the leakages this paper identifies would be to design more macroprudential tools targeting firms, this has been challenging in practice due to heterogeneity of business models across firms.

The rest of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 describes the data sources and explains the construction of the corporate loan growth indicator, macroprudential policy indices and the corporate credit riskiness indicators. Section 4 provides empirical evidence on the portfolio substitution by banks from residential sector to corporate sector. Section 5 documents that such credit allocation is riskier by presenting the results and further robustness checks. Section 6 introduces a simple model of bank portfolio choice to explain our key findings and Section 7 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, 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, Matyunina and Ongena (2022) 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 bank lending. They find that after the new capital requirement was introduced, 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. 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 are three other papers. Cizel et al. (2019) find evidence of substitution of credit from banks towards the non-bank financial sector after macroprudential actions and document that this effect is stronger when the macroprudential policies are binding for banks. In comparison, our paper focuses on the riskiness of credit to corporates, and on portfolio substitution *within* the banking sector. Chakraborty et al. (2018) show that banks that are active in strong housing markets increase mortgage lending and decrease commercial lending. In turn, our results suggest that these effects might be smaller following a tightening of mortgage-specific macroprudential regulations. Another work is 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 the lending standards for loans to large corporates are eased.⁴

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). 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

Bank corporate loan growth. To verify whether macroprudential policy actions affect banks' corporate lending volumes, we check how changes in household-specific regulations impact corporate loan growth depending on banks' exposure to the residential mortgage segment. For this purpose, we collect data on bank-level volumes of corporate and residential mortgage loans from Fitch Connect. We focus on data at annual frequency from 1998 to 2018, since it is more consistent and has better cross-country coverage compared to the data at quarterly frequency. The availability of information on both residential mortgage and corporate lending limits our sample to 13 countries (Brazil, Canada, Chile, China, Finland, Germany, Malaysia, Mexico, Poland, Russia, Spain, Sweden and Thailand). Our variable of interest is *relative corporate loan growth* (CLG), equal to the difference in the annual growth rates in the ratio of corporate loans to total bank loans among the top 30 and bottom 30 percent of banks, when ranked according to the size of their residential mortgage portfolios relative to total loans net of provisions.⁵ Looking at the share of corporate loans in the total bank loan portfolios allows us to capture lending dynamics relative to other loans (housing loans in particular) and thus to account for potential differences in the total lending dynamics between different groups of banks. Nevertheless, as a robustness we also consider the difference in the absolute growth rates of corporate loans between banks most and least exposed to mortgage lending as the dependent variable. We impose a condition of a minimum of 10 bank observations for each country-year and require that each bank has at least 6 years of data.

Corporate credit riskiness. We construct measures of riskiness of corporate credit allocation following Greenwood and Hanson (2013). Their key insight is that cyclical changes

⁴One 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 larger and older corporates which rely more on cash flow-based loans.

⁵Corporate loans category covers loans and leases to corporate and commercial enterprises. These exclude non-residential and commercial property mortgage loans. Residential mortgage loans category covers loans secured by residential property and excludes unsecured loans or loans secured by assets other than residential property.

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. (2019) 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. Brandão-Marques et al. (2019) find that these indicators predict reversals of financial conditions and corporate spreads.

Following this literature, we consider three⁶ measures of riskiness of corporate credit allocation, based on three indicators of firm-level financial vulnerability:

- **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).⁷ 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.

⁶Since the indicator based on Expected Default Frequency(EDF) may be deemed problematic for countries with illiquid equity markets, we focus on three common accounting ratios: debt-to-assets (leverage) ratio, interest coverage ratio (ICR), and debt-to-EBITDA (TDtE) ratio.

⁷Using 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.

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.⁸ 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).⁹ 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

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).

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

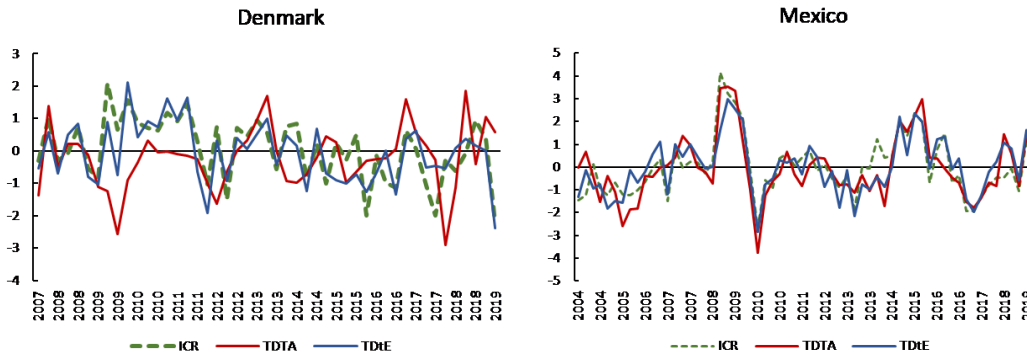
International Monetary Fund (2018) construct the above three measures also using Datastream data but on annual frequency, which allows them to expand the sample to mid-1990s. They find that an increase in the riskiness of credit allocation measures signals heightened downside risks to GDP growth and 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.

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

⁸Country-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.

⁹For additional 8 countries we were able to construct biannual time series.

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



large corporations, allowing us to estimate the leakage effects by the firm size.¹⁰ The data come from the ECB and national authorities 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). The data goes back to 2002-2004 for most of the countries.¹¹ The shortest time series are available for Thailand (2007Q4), Norway (2008Q1), Philippines (2009Q1), Russia (2009Q2). Given a considerable reduction in the sample size when using bank lending standards, we use the three measures of the riskiness of corporate credit allocation in the baseline regressions.

Macroprudential policies. We use the IMF iMaPP database as a source of information on macroprudential policy actions (MaPPs).¹² 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:

- 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 robust-

¹⁰An important caveat is that the criteria for a firm to be classified as a SME vary across countries.

¹¹For Norway and Canada the surveys do not distinguish firms by size.

¹²See Alam et al. (2020) for a description of the database.

ness check, we also use a narrower measure $MaPP^{BC}$ (Alternate), that captures changes in the countercyclical capital buffer, limits on credit growth (overall and corporate sector specific) and restrictions on corporate loan characteristics.

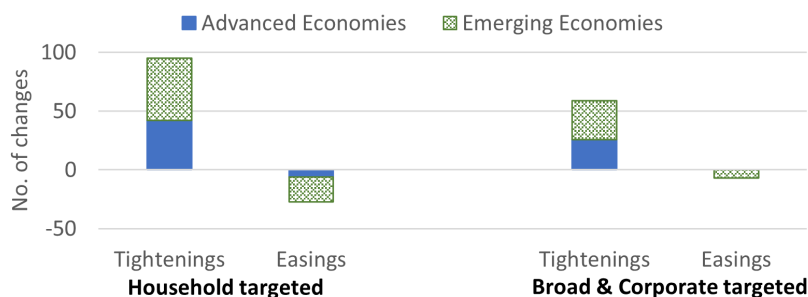
Overall, in the sample of 29 economies for which we were able to construct the riskiness of corporate credit allocation measures, we document 120 changes in baseline measures of household-specific MaPPs, and 66 changes in baseline measures of the broad-based and corporate-specific MaPPs between 2002Q1-2018Q4. 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	-

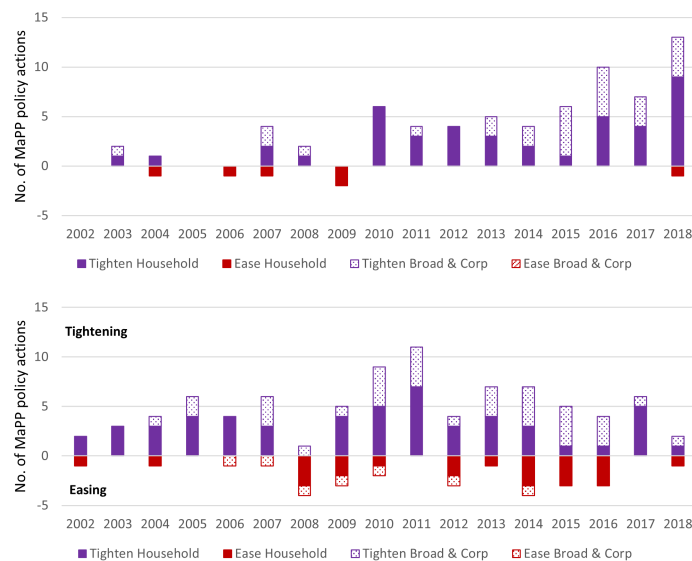
Figure 2 shows that macroprudential policies have been used relatively more in EMs relative to AEs in our sample. For both types of MaPPs, the number of actions (tightening and easing) in EMs are almost double the number of actions in AEs. Separately, MaPP policies were tightened more often (154) as 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 (GFC) period. Instead, year 2018 saw a number of advanced economies tightening LTV and DSTI limits.

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



Source: iMaPP database, authors calculations

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.6, 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.3 describes the methodology for computation of shocks in detail and shows that the main results are robust to using a range of alternative specifications 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.6).

Other variables. We take GDP growth rates and exchange rates from WEO database. Data on credit to the private non-financial sector relative 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.¹³ 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 AREAER report, respectively. Table A1 in the Appendix A.1 lists all data sources and Table A2 contains summary statistics for the key variables used in the analysis.

4 Leakages to Corporate Credit Growth

4.1 Empirical Strategy

We apply panel regressions to study the impact of household-specific macroprudential policy changes on the amount of corporate loans by banks¹⁴. The baseline specification takes the following form:

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

where $CLG_{i,t}$ is a measure of relative growth of corporate loans to total loans in country i in year t and where $\bar{\varepsilon}_{i,t}^{HH}$ and $\bar{\varepsilon}_{i,t}^{BC}$ are macroprudential (household specific and broad-based or corporate specific) policy shocks. A positive (negative) coefficient on a MaPP variable would suggest that an unexpected policy tightening is associated with a larger increase (decline) in the share of corporate loans in total loans for banks more exposed to residential mortgages compared to banks that have smaller exposures. $\Delta Credit_{i,t}$ is the year-on-year growth in the credit-to-GDP ratio¹⁵ as a measure of the stance of the credit cycle. $X_{i,t-1}$ is a vector of control variables that includes year-on-year real GDP growth and domestic currency appreciation against U.S. dollar in the previous year (to control for changes from valuation changes in debt denominated

¹³See International Monetary Fund (2017) and Koop and Korobilis (2014) for details.

¹⁴Given the relatively small sample size, we use standard OLS estimation. With both N and T small, the use of GMM estimation would provide biased estimates.

¹⁵Credit is measured as credit to the private non-financial sector and includes both domestic and cross-border credit flows. We do not distinguish between credit to the household sector versus corporates in order to maximize the number of countries in the sample (making this distinction would cut our sample by half). We also find household credit and corporate credit to be highly correlated with overall credit to the private non-financial sector.

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. Finally, since our dependent variable is available on annual frequency, we aggregate our macroprudential policy shocks to annual frequency as well.¹⁶

Past literature has documented that the effectiveness of the macroprudential policy likely depends on the position of the business and credit cycle (e.g. Cerutti et al. 2017, Araujo et al. 2020). 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.

$$CLG_{i,t} = \alpha + \beta_1 \bar{\varepsilon}_{i,t}^{HH} + \beta_2 \bar{\varepsilon}_{i,t}^{HH} \times \Delta Credit_{i,t} + \beta_3 \bar{\varepsilon}_{i,t}^{BC} + \beta_4 \bar{\varepsilon}_{i,t}^{BC} \times \Delta Credit_{i,t} + \beta_5 \Delta Credit_{i,t} + \beta_6 X_{i,t-1} + \delta_i + \delta_t + \epsilon_{i,t}, \quad (2)$$

In the robustness checks, we consider additional controls: i) nominal short-term market interest rates to account for domestic financial conditions, ii) real growth of *bank* credit to private nonfinancial corporations, and iii) the real growth of credit to households to ensure that the results are not just driven by the higher aggregate credit.

Additionally, we re-run the regressions (1)-(2) with the difference in the absolute corporate loan growth between the banks most and least exposed to mortgage lending as the dependent variable. While focusing at the share of the corporate loans in the total bank loan portfolios allows us to control for potential differences in the overall lending strategies and growth dynamics between different groups of banks, looking at the absolute corporate loan growth is a good robustness check. Finally, we also consider bank-level regressions with the growth in loans to nonfinancial corporates as the dependent variable.

4.2 Results and Robustness: Relative Corporate Loan Growth

Column 1 of Table 4 shows the results from regression (1). Although the coefficient on the standalone household-specific MaPP shock is negative, it is statistically insignificant. At the same time, periods of high credit growth decrease the difference in growth of corporate loans among the banks most and least exposed to residential mortgages. In other words, banks with smaller residential mortgage portfolios experience higher corporate loan growth compared to banks with higher exposures to residential mortgages.

In column 2 of Table 4, we add the interaction of the MaPP shocks and the credit growth as in equation (2), and in columns 3-6 we expand the specification with additional controls: domestic interest rates in Column 3, banks' corporate credit growth and household credit growth in columns 4-6. We find that the standalone household-specific MaPP shocks are negatively associated with the dependent variable. In columns 4-6, this term is statistically significant, implying that an unexpected tightening decreases the difference in corporate loan growth for

¹⁶We do not consider the lagged dependent variable in the regressions as we do not expect an autoregressive nature of the relative corporate loan growth rates on an annual frequency.

banks with high and low exposure to residential mortgages. At the same time, consistently across Columns 2-6 in Table 4, we find that the interaction term of household-specific MaPP shocks and credit growth is positive and statistically significant, indicating the presence of a non-linear relationship. When credit growth is high, banks with larger residential mortgage portfolios experience higher corporate loan growth compared to banks which are less exposed to residential mortgages after an unexpected tightening of household MaPPs. This supports the narrative that the credit leakages to corporate sector are higher for banks more affected by the macroprudential regulations.

Quantitatively, when credit to GDP ratio grows at a rate of one standard deviation above the sample mean, the relative CLG increases by 54 percent of historical standard deviation after a tightening household-specific MaPP shock. When we use the difference in the absolute corporate loan growth between the banks most and least exposed to mortgage lending as the dependent variable, we again find that the interaction term of household-specific MaPP shocks and credit growth in regression(2) is positive and statistically significant, while the standalone household-specific MaPP shocks are negative albeit not statistically significant in neither of specifications (1)-(2). Quantitatively, for the growth rate of credit to GDP ratio of one standard deviation above the sample mean, the difference in the growth rate of corporate loans between banks most exposed to the mortgage sector and banks least exposed to mortgage lending increases by 1 percentage point following an unexpected household-specific MaPP tightening.¹⁷ This shows that the portfolio re-allocation from residential mortgages to corporate loans following a household-specific MaPP tightening can be economically meaningful.

¹⁷The average annual credit to GDP growth in the sample is 2.3%, and the standard deviation is 8.2%. The average difference in the absolute annual growth rate of corporate loans between the top 30 and bottom 30 percent of banks, when ranked according to the size of their residential mortgage portfolios relative to total loans, is -0.5% (with a standard deviation of 2%) implying that on average banks more exposed to the mortgage lending experience a lower growth of their corporate loan books.

Table (4) *Corporate Loan Growth Regressions*

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	$CLG_{i,t}$	$CLG_{i,t}$	$CLG_{i,t}$	$CLG_{i,t}$	$CLG_{i,t}$	$CLG_{i,t}$
$\bar{\varepsilon}_{i,t}^{HH}$	-0.14 (0.34)	-0.63 (0.48)	-0.61 (0.54)	-1.22** (0.53)	-1.33* (0.61)	-1.47* (0.67)
$\bar{\varepsilon}_{i,t}^{BC}$	0.02 (0.62)	-0.02 (0.73)	0.01 (0.75)	0.01 (0.85)	-0.10 (0.90)	-0.08 (0.88)
$\bar{\varepsilon}_{i,t}^{HH} \times \Delta Credit_{i,t}$		15.19** (6.51)	15.30* (7.96)	20.51** (8.61)	22.80** (7.94)	23.56** (8.29)
$\bar{\varepsilon}_{i,t}^{BC} \times \Delta Credit_{i,t}$		4.02 (7.12)	6.44 (8.38)	6.55 (9.44)	14.36 (9.17)	13.65* (7.31)
$\Delta Credit_{i,t}$	-10.41** (3.43)	-13.06** (4.96)	-13.87** (4.77)	-16.07* (8.52)	-15.77* (7.72)	-13.46** (5.48)
$\Delta GDP_{i,t-1}$	0.20 (0.16)	0.23 (0.16)	0.19 (0.15)	0.29* (0.16)	0.22 (0.13)	0.22 (0.16)
$\Delta ER_{i,t-1}$	-0.01 (0.01)	-0.01 (0.01)	0.04 (0.03)	-0.01* (0.01)	0.05 (0.03)	0.04 (0.04)
$\Delta BankCredit_{i,t}$				3.04 (7.61)	3.73 (7.02)	
$\Delta CreditHH_{i,t}$						2.06 (3.34)
$nominalrate_{t-1}$			-0.20** (0.08)		-0.29*** (0.09)	-0.27** (0.11)
Observations	132	132	123	111	102	102
Number of Countries	13	13	12	12	11	11
Adjusted R-squared	0.07	0.08	0.11	0.09	0.22	0.23
Interaction terms	No	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: $\bar{\varepsilon}_t^{HH(BC)}$ is the household (broad and corporate specific) macroprudential policy shock, $\Delta Credit$ is the growth of credit to non-financial private sector relative to GDP, NR is the 3-month nominal domestic market interest rate, ΔER is the rate of appreciation of local currency against USD, ΔGDP is the real GDP growth, $\Delta BankCredit$ is the real growth of credit to private nonfinancial corporations from banks, and $\Delta CreditHH$ is the real growth of credit to households and NPISHs from all sectors

In Section 6, we consider a simple bank portfolio choice model to explain why leakage effects from macroprudential policies could be stronger during credit booms. In the model, a positive risk sentiment among investors reduces bank funding costs and results in higher bank lending. As bank balance sheets expand, the regulatory capital requirements start to bind, generating interdependence between lending and the risk profile of loans in different loan segments. Thus, the model predicts that both the riskiness of bank corporate lending *and* the volume of bank corporate loans increase during credit booms after a tightening of household-specific MaPPs.

Additional regressions We also run bank-level regressions with the year-on-year growth in loans to nonfinancial corporates as the dependent variable. In this case, apart from controlling for country-specific macroeconomic variables and year fixed effects, we include bank-specific controls: i) the ratio of net income to total assets, ii) growth in total loans, iii) the Tier 1 core capital ratio, and iv) the ratio of liquid assets to total assets. The results are shown in Table A3 in the Appendix A.2.

As before, our main variables of interest are the household-specific MaPP shock and its interaction term with credit growth. Thus, to avoid introducing a double interaction term, we run the bank-level regressions for banks with high and low exposure to mortgage loans separately. Specifically, columns 1 and 3 (columns 2 and 4) of Table A3 show results for banks that in a given year are in the bottom 50 percent (top 50 percent) of banks in a given country according to the share of residential loans in the loan portfolio.

When we consider the interaction term of the (lagged) household-specific MaPP shock with the (lagged) year-on-year growth in credit to GDP ratio, the coefficient estimates are not statistically significant. However, when instead we interact the MaPP shocks with the year-on-year growth of *bank credit*, the coefficient on the interaction term is positive and statistically significant in the regression for the banks with higher exposure to residential loans. In other words, a tighter MaPP policy increases lending to nonfinancial corporates when bank credit growth is high, but only by banks that have a high share of residential loans in their portfolios. Comparing the results from the two specifications, it is possible that at the annual frequency (at which bank balance sheet data for a large group of countries are available) growth in bank credit is a better indicator of the cyclical position of the banking sector than the ratio of total credit to GDP and thus more relevant to banks when making their lending decisions. Overall, we take the evidence from the bank-level regressions as supportive of our main findings.

Alternative macroprudential policy shocks. We also consider specifications where the household-specific or broad-based and corporate-specific MaPP shocks are constructed using the alternate $MaPP^{HH}$ and $MaPP^{BC}$ indicators, as described in Section 3. As Table 5 shows, the results are robust to this alternative definitions of MaPP policy indicators. When we analyze leakages from macroprudential policies to corporate credit risk in section 5, we consider a broader range of alternative MaPP shocks. In the case of corporate credit growth, however, the annual frequency and the availability of data on control variables we use to obtain MaPP shocks in the first-stage regressions (Appendix A.3), limit the number of alternative MaPP shocks we can use.

Table (5) *Corporate Loan Growth Regressions: Alternative definitions of MaPP measures*

VARIABLES	(1) <i>CLG</i> _{<i>i,t</i>}	(2) <i>CLG</i> _{<i>i,t</i>}	(3) <i>CLG</i> _{<i>i,t</i>}	(4) <i>CLG</i> _{<i>i,t</i>}
$\bar{\varepsilon}_{i,t}^{HH,Alternate}$	-0.44 (0.39)	-0.45 (0.42)		
$\bar{\varepsilon}_{i,t}^{BC}$	0.33 (0.69)	0.39 (0.72)		
$\bar{\varepsilon}_{i,t}^{HH,Alternate} \times \Delta Credit_{i,t}$	8.16** (2.83)	8.52** (3.05)		
$\bar{\varepsilon}_{i,t}^{BC} \times \Delta Credit_{i,t}$	2.66 (6.97)	4.05 (6.40)		
$\bar{\varepsilon}_{i,t}^{HH}$			-0.77* (0.42)	-0.74 (0.47)
$\bar{\varepsilon}_{i,t}^{BC,Alternate}$			0.39 (0.69)	0.51 (0.69)
$\bar{\varepsilon}_{i,t}^{HH} \times \Delta Credit_{i,t}$			19.71*** (5.10)	19.13*** (6.07)
$\bar{\varepsilon}_{i,t}^{BC,Alternate} \times \Delta Credit_{i,t}$			8.16 (7.44)	8.06 (7.19)
$\Delta Credit_{i,t}$	-13.89** (6.23)	-15.69** (6.01)	-12.26** (5.42)	-14.03** (5.32)
$\Delta GDP_{i,t-1}$	0.17 (0.13)	0.16 (0.13)	0.18 (0.12)	0.16 (0.12)
$\Delta ER_{i,t-1}$	-0.01 (0.01)	0.04 (0.03)	-0.01 (0.01)	0.05 (0.03)
$nominalrate_{i,t-1}$		-0.18** (0.07)		-0.19** (0.06)
Observations	132	123	132	123
Number of Countries	13	12	13	12
Adjusted R-squared	0.08	0.12	0.11	0.14
Interaction terms	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. See notes under Table 4 for variables description.

5 Leakages to Corporate Credit Risk

5.1 Empirical Strategy

To study the impact of household-specific macroprudential policy changes on the riskiness of corporate credit allocation, we use specification similar to (1)-(2) in the previous section:

$$CC_{i,t}^s = \alpha + \gamma CC_{i,t-1}^s + \sum_{k=1}^4 \beta_{1,k} \varepsilon_{i,t-k}^{HH} + \sum_{k=1}^4 \beta_{2,k} \varepsilon_{i,t-k}^{BC} + \beta_3 X_{i,t-1} + \delta_i + \delta_t + \epsilon_{i,t}, \quad (3)$$

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.

Similar to equation (2), we consider an alternative specification, where the macroprudential policy shocks are interacted with the growth in the credit to GDP ratio. To keep the specification tractable, we include only one measure of macroprudential policy shocks, which is the sum of policy shocks in the past four quarters, and its interaction with the credit-to-GDP growth:

$$CC_{i,t}^s = \alpha + \gamma CC_{i,t-1}^s + \beta_1 \bar{\varepsilon}_{i,t-1}^{HH} + \beta_2 \bar{\varepsilon}_{i,t-1}^{HH} \times \Delta \text{Credit}_{i,t-1} + \beta_3 \bar{\varepsilon}_{i,t-1}^{BC} + \beta_4 \bar{\varepsilon}_{i,t-1}^{BC} \times \Delta \text{Credit}_{i,t-1} + \beta_5 X_{i,t-1} + \delta_i + \delta_t + \epsilon_{i,t}, \quad (4)$$

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 $\Delta \text{Credit}_{i,t}$ stands for year-on-year growth in the credit-to-GDP ratio in country i in quarter t .

5.2 Baseline 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 A10 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 when credit growth has been rapid in the recent past. This is consistent with past literature discussed in Section 2.

Results from the baseline specification (3) are shown in columns 1-3 of Table 6. Among 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.

Table (6) *Baseline Regressions*

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	TDTA	ICR	TDtE	TDTA	ICR	TDtE
<i>Dependent Variable</i> $e_{i,t-1}$	0.486*** (0.042)	0.328*** (0.040)	0.385*** (0.037)	0.487*** (0.043)	0.326*** (0.040)	0.381*** (0.037)
$\varepsilon_{i,t-1}^{HH}$	0.004 (0.041)	-0.061 (0.044)	-0.061 (0.047)			
$\varepsilon_{i,t-2}^{HH}$	0.057 (0.044)	0.008 (0.046)	-0.044 (0.050)			
$\varepsilon_{i,t-3}^{HH}$	0.116** (0.044)	-0.012 (0.069)	-0.023 (0.057)			
$\varepsilon_{i,t-4}^{HH}$	0.004 (0.045)	0.064 (0.044)	0.062 (0.054)			
$\varepsilon_{i,t-1}^{BC}$	0.064 (0.122)	0.087 (0.117)	0.113 (0.157)			
$\varepsilon_{i,t-2}^{BC}$	0.096 (0.110)	0.004 (0.112)	0.058 (0.137)			
$\varepsilon_{i,t-3}^{BC}$	-0.118 (0.119)	-0.080 (0.128)	-0.000 (0.135)			
$\varepsilon_{i,t-4}^{BC}$	-0.102 (0.097)	-0.156 (0.133)	-0.193 (0.134)			
$\bar{\varepsilon}_{i,t-1}^{HH}$				0.020 (0.024)	-0.029 (0.032)	-0.067* (0.038)
$\bar{\varepsilon}_{i,t-1}^{BC}$				0.026 (0.045)	0.019 (0.065)	0.023 (0.078)
$\bar{\varepsilon}_{i,t-1}^{HH} \times \Delta Credit_{i,t-1}$				0.012** (0.005)	0.014* (0.007)	0.022** (0.008)
$\bar{\varepsilon}_{i,t-1}^{BC} \times \Delta Credit_{i,t-1}$				-0.018* (0.010)	-0.022 (0.019)	-0.015 (0.014)
$\Delta Credit_{i,t-1}$	0.021*** (0.005)	0.025*** (0.008)	0.032*** (0.007)	0.019*** (0.006)	0.022** (0.009)	0.028*** (0.008)
$\Delta GDP_{i,t-1}$	0.044*** (0.010)	0.034*** (0.012)	0.057*** (0.015)	0.041*** (0.010)	0.031** (0.012)	0.055*** (0.015)
$\Delta_q ER_{i,t-1}$	-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 Countries	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.

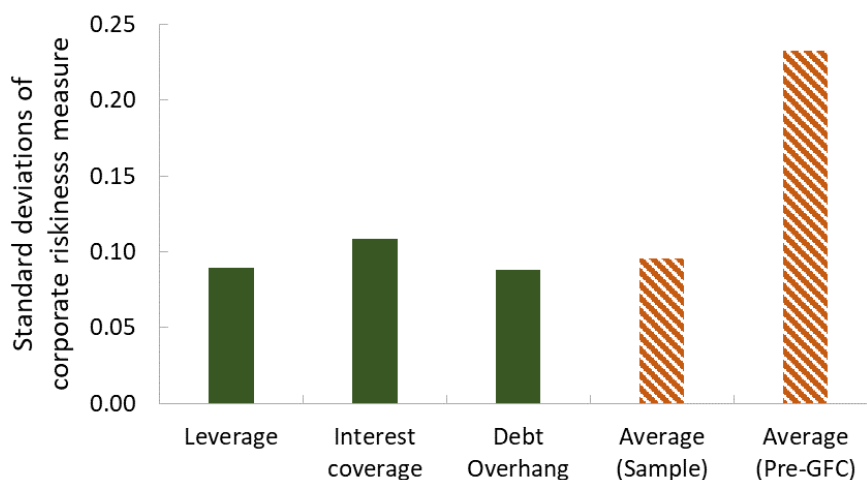
The first column of Table 6 shows the effect of an unexpected tightening of macroprudential measures on the leverage-based measure of corporate credit riskiness (TDTA). All lags of the household-specific MaPPs are positive, indicating that an unexpected tightening would be associated with an increase 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 either type of MaPPs are not jointly statistically significant. Columns 2 and 3 of Table 6 show results for the other two riskiness indicators (ICR and TDtE), where the lags of MaPP shocks are again not statistically significant.

Columns 4-6 of Table 6 show the results of the alternative specification (4), where MaPP shocks are interacted with the credit to GDP growth to allow for non-linear effects of policies depending on the stage of the credit cycle. 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 in the short term, on average across measures. At the same time, when 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.¹⁸ The average long-run effect of an unexpected tightening in the household-specific MaPPs when credit relative to GDP grows at a rate of one standard deviation above the sample mean is around 16 percent of the standard deviation across the three riskiness measures.

Digging deeper into the magnitude of this effect, 19 percent of the country-quarter observations in our sample record credit to GDP growth rates of more than one standard deviation above the sample mean (29 percent for the emerging economies and 10 percent of quarters for the advanced economies). Importantly, in the pre-GFC period of 2005-2008—known for rapid credit growth and for the build-up of financial vulnerabilities—the average year-on-year growth rate of credit to GDP across countries was 14 percent, while the three riskiness measures increased during the same time by around 80 percent of a standard deviation over the same period, on average across countries. Thus, the leakages we document are considerable in magnitude. In fact, for the credit growth of 14 percent in the pre-GFC period, the size of direct (short-term) leakages from an unexpected household-specific MaPP tightening would be 23 percent of a historical standard deviation across the corporate credit riskiness measures.

¹⁸As we show in Section 6, improved risk sentiment among bank creditors can lead to an expansion of bank balance sheets and result in binding regulatory requirements. Under these circumstances, banks' lending decisions in different loan segments become interdependent and a tightening of requirements for one loan type can affect the amount and the risk profile of loans in other loan segments.

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



Note: Green bars measure the impact of a household-specific macroprudential tightening on each of the three corporate riskiness measures when credit growth is 1 standard deviation above its mean. Bars with orange stripes represent the average impact across these measures for the full sample period and, as a reference, the implied impact during the pre-GFC period.

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 only for the TDTA measure. This result suggests that the effectiveness of those MaPP measures in reducing riskiness of credit in the corporate sector might be limited, for example on the account of easier access to less regulated (non-bank) sources of funding compared to households.

5.3 Robustness

We conduct a broad range of robustness exercises. Tables 7-9 present a sample of them, for each of the three credit riskiness measures. Our starting point is the specification (4) that includes the interaction term between the macroprudential variables and the growth rate of the credit to GDP ratio.

Column 1 in Tables 7-9 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, in line with expectation 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 7-9).

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 macropru-

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

VARIABLES	(1) TDTA	(2) TDTA	(3) TDTA	(4) TDTA	(5) TDTA	(6) TDTA
$TDTA_{i,t-1}$	0.49*** (0.04)	0.50*** (0.05)	0.47*** (0.05)	0.47*** (0.05)	0.52*** (0.02)	0.48*** (0.04)
$\bar{\varepsilon}_{i,t-1}^{HH}$	0.02 (0.03)	0.02 (0.03)	0.03 (0.03)	0.04 (0.08)	-0.02 (0.05)	0.02 (0.03)
$\bar{\varepsilon}_{i,t-1}^{BC}$	0.02 (0.05)	-0.01 (0.04)	0.00 (0.05)	-0.04 (0.10)	0.01 (0.04)	0.03 (0.05)
$\bar{\varepsilon}_{i,t-1}^{HH} \times \Delta Credit_{i,t-1}$	0.01* (0.01)	0.01* (0.01)	0.01** (0.01)	0.01 (0.01)	0.02*** (0.01)	0.01* (0.01)
$\bar{\varepsilon}_{i,t-1}^{BC} \times \Delta Credit_{i,t-1}$	-0.02* (0.01)	-0.02 (0.01)	-0.03** (0.01)	-0.02 (0.01)	-0.02* (0.01)	-0.02* (0.01)
$\Delta Credit_{i,t-1}$	0.01** (0.01)	0.01 (0.01)	0.02** (0.01)	0.01* (0.01)	0.01* (0.00)	0.01** (0.01)
$\Delta GDP_{i,t-1}$	0.03** (0.01)	0.04*** (0.01)	0.04*** (0.01)	0.04*** (0.01)	0.03** (0.01)	0.03** (0.01)
$\Delta_q ER_{i,t-1}$	-0.02** (0.01)	-0.02** (0.01)	-0.02** (0.01)	-0.02*** (0.01)	-0.02** (0.01)	-0.02*** (0.01)
$FCI_{i,t-1}$	-0.13** (0.05)	-0.15*** (0.04)	-0.07 (0.05)	-0.07 (0.05)	-0.14** (0.06)	-0.12* (0.06)
$GlobalVolatility_{t-1}$		0.10*** (0.03)				
Δffr_{t-1}		-0.00 (0.04)				
$\Delta NFCBonds_{i,t-1}$			-0.03 (0.05)			
$\bar{\varepsilon}_{i,t-1}^{HH} \times \Delta NFCBonds_{i,t-1}$			-0.16 (0.09)			
$\bar{\varepsilon}_{i,t-1}^{BC} \times \Delta NFCBonds_{i,t-1}$			0.53 (0.37)			
$BondsCredit_{i,t-1}^{ma}$				-0.01 (0.00)		
$\bar{\varepsilon}_{i,t-1}^{HH} \times BondsCredit_{i,t-1}^{ma}$				-0.00 (0.00)		
$\bar{\varepsilon}_{i,t-1}^{BC} \times BondsCredit_{i,t-1}^{ma}$				0.01 (0.01)		
$\Delta HPI_{i,t-1}$						0.00 (0.00)
Observations	1,108	1,108	1,026	1,013	924	1,108
Number of Countries	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 - $GlobalVolatility$ stands for MSCI World Index, Δffr is the quarterly change in the Fed funds rate/ 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, $BondsCredit^{ma}$ 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 (8) *Robustness: TDtE measure of credit riskiness*

VARIABLES	(1) TDtE	(2) TDtE	(3) TDtE	(4) TDtE	(5) TDtE	(6) TDtE
$TDtE_{i,t-1}$	0.36*** (0.03)	0.37*** (0.04)	0.36*** (0.04)	0.35*** (0.04)	0.37*** (0.03)	0.36*** (0.03)
$\bar{\varepsilon}_{i,t-1}^{HH}$	-0.09** (0.04)	-0.07* (0.04)	-0.09** (0.04)	0.00 (0.08)	-0.05 (0.06)	-0.09** (0.04)
$\bar{\varepsilon}_{i,t-1}^{BC}$	0.02 (0.08)	0.05 (0.09)	-0.03 (0.10)	-0.05 (0.10)	0.01 (0.08)	0.02 (0.08)
$\bar{\varepsilon}_{i,t-1}^{HH} \times \Delta Credit_{i,t-1}$	0.02*** (0.01)	0.02** (0.01)	0.02*** (0.01)	0.02** (0.01)	0.02** (0.01)	0.02*** (0.01)
$\bar{\varepsilon}_{i,t-1}^{BC} \times \Delta Credit_{i,t-1}$	-0.01 (0.01)	-0.02 (0.01)	-0.04** (0.02)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)
$\Delta Credit_{i,t-1}$	0.02** (0.01)	0.02*** (0.01)	0.02** (0.01)	0.02* (0.01)	0.02** (0.01)	0.02** (0.01)
$\Delta GDP_{i,t-1}$	0.05** (0.02)	0.04*** (0.02)	0.05*** (0.02)	0.05** (0.02)	0.04** (0.02)	0.05*** (0.02)
$\Delta_q ER_{i,t-1}$	0.00 (0.01)	0.01 (0.01)	0.00 (0.01)	-0.00 (0.01)	0.00 (0.01)	0.00 (0.01)
$FCI_{i,t-1}$	-0.21** (0.08)	-0.17** (0.07)	-0.16* (0.09)	-0.16 (0.10)	-0.22** (0.09)	-0.21** (0.09)
$GlobalVolatility_{t-1}$		0.07* (0.03)				
Δffr_{t-1}		-0.02 (0.06)				
$\Delta NFCBonds_{i,t-1}$			0.00 (0.03)			
$\bar{\varepsilon}_{i,t-1}^{HH} \times \Delta NFCBonds_{i,t-1}$			-0.08 (0.08)			
$\bar{\varepsilon}_{i,t-1}^{BC} \times \Delta NFCBonds_{i,t-1}$			1.15** (0.55)			
$BondsCredit_{i,t-1}^{ma}$				-0.01 (0.01)		
$\bar{\varepsilon}_{i,t-1}^{HH} \times BondsCredit_{i,t-1}^{ma}$				-0.00 (0.00)		
$\bar{\varepsilon}_{i,t-1}^{BC} \times BondsCredit_{i,t-1}^{ma}$				0.01 (0.01)		
$\Delta HPI_{i,t-1}$						0.00 (0.01)
Observations	1,098	1,098	1,017	1,003	921	1,098
Number of Countries	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 - *GlobalVolatility* stands for MSCI World Index, Δffr is the quarterly change in the Fed funds rate/ 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, $BondsCredit^{ma}$ 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 (9) *Robustness: ICR measure of credit riskiness*

VARIABLES	(1) ICR	(2) ICR	(3) ICR	(4) ICR	(5) ICR	(6) ICR
$ICR_{i,t-1}$	0.32*** (0.04)	0.33*** (0.04)	0.31*** (0.05)	0.30*** (0.04)	0.33*** (0.04)	0.32*** (0.04)
$\bar{\varepsilon}_{i,t-1}^{HH}$	-0.05 (0.04)	-0.03 (0.03)	-0.05 (0.04)	0.06 (0.09)	-0.04 (0.07)	-0.05 (0.04)
$\bar{\varepsilon}_{i,t-1}^{BC}$	0.01 (0.07)	0.03 (0.06)	-0.02 (0.08)	-0.10 (0.09)	0.01 (0.07)	0.01 (0.07)
$\bar{\varepsilon}_{i,t-1}^{HH} \times \Delta Credit_{i,t-1}$	0.02* (0.01)	0.01* (0.01)	0.02* (0.01)	0.01 (0.01)	0.02* (0.01)	0.02* (0.01)
$\bar{\varepsilon}_{i,t-1}^{BC} \times \Delta Credit_{i,t-1}$	-0.02 (0.02)	-0.03 (0.02)	-0.04** (0.02)	-0.02 (0.02)	-0.02 (0.02)	-0.02 (0.02)
$\Delta Credit_{i,t-1}$	0.01 (0.01)	0.02* (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01* (0.01)
$\Delta GDP_{i,t-1}$	0.02 (0.02)	0.02 (0.02)	0.03 (0.02)	0.02 (0.02)	0.01 (0.02)	0.02 (0.01)
$\Delta_q ER_{i,t-1}$	0.00 (0.01)	0.01 (0.01)	0.00 (0.01)	0.00 (0.01)	0.01 (0.01)	0.00 (0.01)
$FCI_{i,t-1}$	-0.20** (0.08)	-0.17** (0.06)	-0.15* (0.08)	-0.15* (0.09)	-0.21** (0.09)	-0.21** (0.09)
$GlobalVolatility_{t-1}$		0.11*** (0.04)				
Δffr_{t-1}		-0.04 (0.06)				
$\Delta NFCBonds_{i,t-1}$			0.00 (0.03)			
$\bar{\varepsilon}_{i,t-1}^{HH} \times \Delta NFCBonds_{i,t-1}$			-0.11 (0.11)			
$\bar{\varepsilon}_{i,t-1}^{BC} \times \Delta NFCBonds_{i,t-1}$			0.99* (0.48)			
$BondsCredit_{i,t-1}^{ma}$				-0.01 (0.00)		
$\bar{\varepsilon}_{i,t-1}^{HH} \times BondsCredit_{i,t-1}^{ma}$				-0.00 (0.00)		
$\bar{\varepsilon}_{i,t-1}^{BC} \times BondsCredit_{i,t-1}^{ma}$				0.01 (0.01)		
$\Delta HPI_{i,t-1}$						-0.00 (0.01)
Observations	1,108	1,108	1,026	1,013	924	1,108
Number of Countries	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 - $GlobalVolatility$ stands for MSCI World Index, Δffr is the quarterly change in the Fed funds rate/ 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, $BondsCredit^{ma}$ 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.

dential policy measures affect bank lending only. There are, however, several channels through which household-specific MaPPs binding for banks only, could affect non-bank corporate 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 7-9) or ii) a four-quarter moving average of the ratio of outstanding corporate bonds to outstanding corporate bank credit (column 4 in Tables 7-9), 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 tighter 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 7-9 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 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 7-9 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.

Table (10) *Alternative definitions of MaPP measures*

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

Alternative macroprudential policy shocks. In the Appendix A.3 we show that the main results are robust to using a range of alternative first-stage regressions to derive macropru-

dential shocks. While in the baseline specification, we use MaPP shocks from probit regressions on 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, in the alternative specifications of the first-stage regressions we also control for i) domestic interest rates, ii) the lagged moving average of the corporate credit riskiness measures, iii) house prices and credit growth rates over 1 or 2 years instead of quarter-on-quarter, iv) credit to households and credit to nonfinancial corporates separately. Tables A7-A9 show the estimates of regression (4) when using those alternative MaPP shocks. Finally, in a separate exercise we also replace our MaPP shocks with shocks constructed using the alternate indicators of $MaPP^{HH}$ and $MaPP^{BC}$, as explained in Section 3. Table 10 shows the results.

Additional robustness exercises. In Appendices A.5 and A.6 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.¹⁹ We also verify that all the results hold when using the pooled mean group estimator of Pesaran, Shin, and Smith (1997, 1999) that allows for heterogeneity in error variances across countries.

5.4 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. This allows us to focus on bank credit availability more explicitly as compared to the corporate credit riskiness indicators constructed in Section 3.²⁰ 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 11 show the results from the baseline regression (3) for all corporations, SMEs and to large corporates respectively.²¹ Columns 2, 4 and 6 in Table 11 further control for domestic conditions using the local 3-month money market rates.²² 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.

¹⁹In all regressions we include time fixed effects, which should mitigate the cross-section correlation concerns.

²⁰While many central banks use loan officer surveys to gauge the extent of tightening or relaxing lending standards, a potential concern might be that respondents could strategically offer responses consistent with outcomes desired by the central banks or bank supervisors rather than actual changes in lending standards.

²¹We also ran the regression (4) 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.

²²We use the 3-month market rates instead of domestic FCI to maximize the number of countries in the sample.

Table (11) *Bank Lending Standards for Corporate Loans*

VARIABLES	(1) LS(All)	(2) LS(All)	(3) LS(SMEs)	(4) LS(SMEs)	(5) LS(Large)	(6) LS(Large)
<i>DependentVariable</i> $\varepsilon_{i,t-1}$	0.716*** (0.068)	0.716*** (0.070)	0.680*** (0.079)	0.681*** (0.082)	0.680*** (0.080)	0.675*** (0.086)
$\varepsilon_{i,t-1}^{HH}$	1.301** (0.576)	1.302** (0.591)	1.897* (1.034)	1.892* (1.045)	0.043 (0.743)	0.076 (0.745)
$\varepsilon_{i,t-2}^{HH}$	-1.216 (0.744)	-1.216 (0.744)	-1.351 (0.880)	-1.352 (0.880)	-0.991 (0.872)	-0.990 (0.876)
$\varepsilon_{i,t-3}^{HH}$	-0.503 (0.737)	-0.503 (0.741)	0.687 (1.010)	0.687 (1.011)	-1.616* (0.869)	-1.615* (0.863)
$\varepsilon_{i,t-4}^{HH}$	-1.440 (0.916)	-1.440 (0.915)	-0.037 (0.934)	-0.041 (0.929)	-0.783 (0.815)	-0.774 (0.830)
$\varepsilon_{i,t-1}^{BC}$	-1.140 (0.900)	-1.140 (0.979)	-2.258 (1.758)	-2.263 (1.770)	-2.051* (1.025)	-2.010* (1.125)
$\varepsilon_{i,t-2}^{BC}$	-1.731 (1.348)	-1.730 (1.352)	-0.036 (1.425)	-0.041 (1.430)	-2.483 (1.881)	-2.448 (1.895)
$\varepsilon_{i,t-3}^{BC}$	-0.680 (1.944)	-0.679 (1.805)	0.616 (1.261)	0.597 (1.220)	0.570 (2.174)	0.682 (1.985)
$\varepsilon_{i,t-4}^{BC}$	-1.605 (1.498)	-1.604 (1.660)	-2.569* (1.297)	-2.589* (1.447)	-0.382 (1.930)	-0.261 (2.087)
$\Delta Credit_{i,t-1}$	0.177* (0.095)	0.177* (0.100)	0.251** (0.108)	0.254** (0.112)	0.157 (0.128)	0.139 (0.137)
$\Delta GDP_{i,t-1}$	0.344* (0.193)	0.344** (0.151)	0.310 (0.242)	0.302 (0.185)	0.365 (0.252)	0.414 (0.255)
$\Delta_q ER_{i,t-1}$	0.166 (0.132)	0.166 (0.117)	0.079 (0.148)	0.076 (0.132)	0.002 (0.123)	0.023 (0.115)
<i>nominalrate</i> $\varepsilon_{i,t-1}$		0.003 (0.539)		-0.053 (0.560)		0.335 (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

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. *Nominalrate* is the 3-month nominal domestic market interest rate.

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 et al. 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 et al. (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.

6 A model of bank portfolio choice

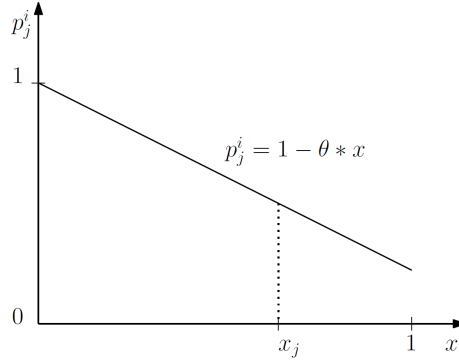
In this Section, we consider a simple model of bank portfolio choice that can account for the main findings of our analysis, i.e. leakages from household-specific MaPPs to corporate lending (both in terms of loan volumes and riskiness of new lending) during the credit booms.

In the model, there is a unit mass of risk-neutral banks that invest in risky projects on behalf of investors. There are two dates: at date 0 the representative bank decides how much to invest in the projects, at date 1 all returns are realized and bank creditors are repaid accordingly.

Investment opportunities. There are two types of projects: A (corporate) and B (retail), each in a unit mass supply. When successful, each project i of type A generates a return $r_A > 1$ and each project of type B generates a return $r_B > 1$. Within each type, the projects differ in terms of the probability of being successful, p_k^i , with $k = \{A, B\}$. The probability of delivering a positive return is such that it declines for each additional project being funded. In particular, denote by $x_A \in [0, 1]$ the mass of A-type projects funded by the representative bank, and by $x_B \in [0, 1]$ the mass of B-type projects funded. If we order the projects according to their (declining) success of probability, then the marginal project A has a probability of success equal $p_A^{x_A} = 1 - \theta x_A$. For the marginal B-type project this probability is $p_B^{x_B} = 1 - \theta x_B$, with $\theta \in (0, 1)$.

For now we keep θ fixed. As we will show below, allowing θ to vary with the risk perceptions among banks and their investors can generate interdependence between investments in portfolios A and B. Figure 5 plots the success probabilities as a function of the size of the project book.

Figure (5) Probability of a positive return of project $j \in \{A, B\}$.



It follows that the expected return on the representative bank's portfolio A of size x_A is:

$$E[\pi_A(x_A)] = \int_0^{x_A} r_A(1 - \theta x) dx = r_A x_A \left(1 - \frac{\theta}{2} x_A\right). \quad (5)$$

Accordingly, for the bank's portfolio B of size x_B , the expected return is $E[\pi_B(x_B)] = r_B x_B \left(1 - \frac{\theta}{2} x_B\right)$.

Funding structure. The representative bank finances its investments, $x_A + x_B$, through equity K and deposits D . Deposits are fully insured and thus yield a rate of return equal to the return on a storage technology, $r_D = 1$. Equity is costly for the bank, as bank shareholders require a positive rate of return, $r_K > 1$.²³

Banks are also subject to minimum capital requirements $k_A \in (0, 1)$ and $k_B \in (0, 1)$, imposing a minimum share of projects A and B to be funded with equity: $K_A \geq k_A x_A$ and $K_B \geq k_B x_B$.²⁴ Since $r_K > r_D$, the bank will always prefer to fund its operations with deposits than with more expensive equity and the capital requirements will always be binding.

The maximum amount of funds—in the form of deposits or equity—available for the banks to finance the projects is limited to I :

$$x_A + x_B \leq I. \quad (6)$$

Bank optimization problem. The representative bank chooses x_A and x_B to maximize:

$$\max_{x_A, x_B} E[\pi_A(x_A)] + E[\pi_B(x_B)] - [r_D(1 - k_A) + r_K k_A] x_A - [r_D(1 - k_B) + r_K k_B] x_B, \quad (7)$$

subject to (6). The terms $r_D(1 - k_A) + r_K k_A$ and $r_D(1 - k_B) + r_K k_B$ stand for the unit funding costs for projects A and B, respectively, where we use that the capital requirements are always binding. The solution to the optimization problem (7) depends on whether the resource

²³In this simple way we capture the well-documented preference of financial intermediaries for debt funding. Note that while we do not have aggregate uncertainty in the model, a positive r_K could emerge in the presence of aggregate risk even if bank shareholders are risk-neutral.

²⁴While we do not microfound the reasons for the introduction of capital requirements, one can think of regulations emerging as an attempt of the regulators to limit the costs of providing deposit insurance when bank managers are protected by limited liability.

constraint (6) binds or not.

Case I: $x_A + x_B < I$. It is straightforward to show that when the bank is not constrained by the supply of funding, investments in the two portfolios A and B are independent of each other and equal to:

$$x_A^* = \frac{r_A - 1 - k_A(r_K - 1)}{\theta r_A}, \quad (8)$$

and

$$x_B^* = \frac{r_B - 1 - k_B(r_K - 1)}{\theta r_B}. \quad (9)$$

The size of each portfolio increases with the expected return, declines with the level of the capital requirement and with the return on equity. At the same time, the probability of success of a marginal project in each of the two portfolios, $1 - x_j$ with $j \in \{A, B\}$, and the average probability of success of a project in a portfolio both decline in the size of the investment.

Case II: $x_A + x_B = I$. When the bank hits the limit I of funds available from investors, a simple substitution of $x_B = I - x_A$ yields the following solution:

$$x_A^* = \frac{r_A - r_B + r_B I - (k_A - k_B)(r_K - 1)}{\theta(r_A + r_B)}, \quad (10)$$

and

$$x_B^* = I - x_A^*. \quad (11)$$

A higher investment in A-type projects reduces investment in B-type projects and vice-versa. Additionally, a higher capital requirement on B-type (retail) projects increases bank's investment in projects A (corporate loans) and reduces the probability of success of a marginal project A (and the average probability of success of type-A projects in the portfolio), since $\frac{dx_A^*}{dk_B} > 0$. Lemma 1 summarizes the two cases.

***Lemma 1.** When banks are not financially constrained, investments and riskiness of loans in portfolios A and B are independent of each other. When the supply of bank funding is limited, investment decisions become interdependent. A higher capital requirement for one loan portfolio increases investment and riskiness of loans in the other portfolio.*

Changes in risk sentiment and bank investment choices. We now demonstrate how changes in the risk sentiment among banks (and their creditors) can cause a switch of our simple economy from case I to case II. Suppose that the parameter θ driving the success probability of projects A and B can take one of two values, θ^L and θ^H , with $\theta^L < \theta^H$. A high value of θ could be interpreted as reflecting the bad states of the world, and a low value as reflecting good aggregate economic conditions. Additionally, before investing in projects A and B, bank managers and bank creditors observe a signal $\hat{\theta} \in \{\hat{\theta}^H, \hat{\theta}^L\}$ about the true value of θ . For simplicity we consider $\hat{\theta}$ to be a perfect signal, $\hat{\theta} = \theta$, but in principle it could be associated with some error. In this case, changes in the $\hat{\theta}$, i.e. changes in the risk sentiment (or risk perceptions) would drive the investment decisions.

It is straightforward to demonstrate that with a time-varying θ , the following Lemma holds.²⁵

Lemma 2. *Bank investments in portfolios A and B decline in θ . Define $\bar{\theta}$ as*

$$\bar{\theta} = \frac{r_A - 1 - k_A(r_K - 1)}{r_A I} + \frac{r_B - 1 - k_B(r_K - 1)}{r_B I}. \quad (12)$$

If $\theta^L < \bar{\theta} < \theta^H$, the resource constraint binds in good states of the world and it does not bind in the bad states of the world. As a result i) bank credit is procyclical, and ii) a rise in capital requirements for one portfolio leads to an increase in the size of lending and in the riskiness of loans in the other portfolio only in the good states of the world.

7 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 document leakages in terms of the volume of new bank credit to the corporate sector and in terms of the risk profile of credit allocated to corporate firms.

First, using bank-level data on loan volumes we show that after an unexpected tightening of household-specific MaPPs during credit expansions, banks with higher exposures to residential mortgages experience much higher corporate loan growth compared to banks which are less exposed to residential mortgages. In other words, leakages from sector-specific MaPPs are higher for banks more affected by the regulations.

Next, 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 during credit expansions. The effects are economically meaningful: an unexpected tightening in the household-specific policies increases the credit riskiness measures by an average of 10 percent of their historical standard deviations when the credit to GDP ratio grows at a rate one standard deviation above its mean. When replacing our corporate credit riskiness indicators with 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. This further corroborates our hypothesis that as regulations start binding in household sector, the riskiness profile of corporate borrowers deteriorates.

Overall, our paper provides evidence that the cross-sectoral leakages from macroprudential policies might be quantitatively important. Thus, such effects should be considered by the

²⁵Another channel through which better economic outlook could affect the bindness of the resource constraint for banks is a time-varying rate of return on equity r_K . Empirically it is found to be lower during economic upswings, and to increase during downturns (see e.g. Yang and Tsatsaronis (2012)).

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 growing but likely to be still low. To avoid large and unwanted leakage effects, timely monitoring of vulnerabilities in both household and corporate sectors is key. For the corporate sector, our results suggest that information on the distribution of the firm loans by the firm size in bank loan portfolios might be relevant for assessing the size of potential leakage effects. While an alternative way to address the leakages we identify would be to design macroprudential tools explicitly for the corporates, so far this has been very difficult to implement in practice, due to heterogeneity of business models across firms.

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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 exchange rate against USD	growth rates	WEO database
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
residential mortgage loans, corporate and commercial loans	bank balance sheet variables needed to compute the CLG indicator	Fitch Connect

Table (A2) *Summary statistics for key variables*

Variable	Definition	Obs.	Mean	Std. dev.	Min	Max
<i>CLG</i>	Relative corp. loan growth	132	-0.14	1.99	-5.00	5.67
<i>TDTA</i>	Corp. credit riskiness measure	1,726	-0.03	0.93	-3.02	3.11
<i>ICR</i>	Corp. credit riskiness measure	1,726	0.01	0.88	-3.02	3.30
<i>TDtE</i>	Corp. credit riskiness measure	1,713	0.01	0.92	-3.40	3.18
<i>LS(All)</i>	Bank lending standards: All NFCs	943	4.04	17.88	-49.64	91.00
<i>LS(Large)</i>	Bank lending standards: Large Firms	831	4.84	17.81	-44.40	90.50
<i>LS(SMEs)</i>	Bank lending standards: SMEs	831	3.97	17.51	-46.70	91.00
$\Delta Credit$	Y-o-y credit to GDP growth rate	1,901	2.34	8.20	-43.82	96.76
ΔGDP	Y-o-y real GDP growth rate	1,904	3.17	3.41	-15.22	15.30
$\Delta_q ER$	Q-o-q exchange rate growth rate	1,972	-0.35	5.51	-91.27	15.34
ΔHPI	Y-o-y real HPI growth rate	1,542	2.28	7.12	-28.56	51.68
$\Delta Credit HH$	Y-o-y growth rate of credit to HHs	1,650	4.42	11.11	-47.06	105.00
$\Delta Credit NFC$	Y-o-y growth rate of credit to NFCs	1,650	1.53	9.17	-44.07	126.16
<i>BondCredit^{ma}</i>	Corporate loans to credit ratio (4q ma)	1,499	16.44	14.52	0	76.64
<i>FCI</i>	domestic financial conditions index	1,632	0.00	0.68	-1.38	3.81
<i>nominalrate</i>	3m money market rate	1,900	4.23	4.88	-0.57	61.88

A.2 Corporate Loan Growth: Additional Regressions

Table (A3) *Bank-level regressions for loans to nonfinancial corporates.*

VARIABLES	(1) $\Delta CreditNFC_{i,t}^j$: bottom 50%	(2) $\Delta CreditNFC_{i,t}^j$: top 50%	(3) $\Delta CreditNFC_{i,t}^j$: bottom 50%	(4) $\Delta CreditNFC_{i,t}^j$: top 50%
$\bar{\varepsilon}_{i,t-1}^{HH}$	2.30 (3.04)	-0.01 (0.06)	0.84 (2.67)	-0.11 (0.08)
$\bar{\varepsilon}_{i,t-1}^{BC}$	-3.95 (11.44)	-0.15 (0.26)	-1.88 (14.49)	-0.05 (0.26)
$\bar{\varepsilon}_{i,t-1}^{HH} \times \Delta Credit_{i,t-1}$	-2.17 (47.12)	0.72 (0.79)		
$\bar{\varepsilon}_{i,t-1}^{BC} \times \Delta Credit_{i,t-1}$	9.39 (89.21)	2.79 (5.48)		
$\Delta Credit_{i,t-1}$	23.18 (48.76)	0.90 (0.67)		
$\bar{\varepsilon}_{i,t-1}^{HH} \times \Delta BankCredit_{i,t-1}$			7.49 (15.78)	1.14** (0.41)
$\bar{\varepsilon}_{i,t-1}^{BC} \times \Delta BankCredit_{i,t-1}$			-30.04 (139.98)	0.90 (2.60)
$\Delta BankCredit_{i,t-1}$			-34.06 (72.45)	2.12 (1.44)
$\Delta GDP_{i,t-1}$	0.75 (2.25)	0.03 (0.04)	0.91 (2.15)	0.00 (0.06)
$\Delta ER_{i,t-1}$	0.39 (0.63)	-0.00 (0.03)	-0.17 (0.57)	-0.01 (0.03)
Income to Assets Ratio $_{i,t-1}^j$	-43.98 (77.25)	14.95 (11.27)	-36.59 (71.27)	14.32 (10.93)
$\Delta Loans_{i,t-1}^j$	-16.45 (18.02)	-1.30*** (0.28)	-15.83 (17.36)	-1.33*** (0.26)
Core Capital Ratio $_{i,t-1}^j$	-2.43 (2.66)	0.00 (0.02)	-2.48 (2.69)	0.00 (0.01)
Liquid Assets Ratio $_{i,t-1}^j$	0.44 (0.53)	-0.00 (0.01)	0.46 (0.55)	-0.00 (0.01)
Observations	2,105	2,042	2,105	2,057
Number of banks	833	771	833	775
Adjusted R-squared	0.03	0.00	0.03	0.00
Interaction terms	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The dependent variable, $\Delta CreditNFC_{i,t}^j$ is year-on-year growth in the credit to nonfinancial corporates in year t and country i by bank j . $\bar{\varepsilon}_{i,t}^{HH(BC)}$ is the sum of household-specific (broad-based or corporate-specific) MaPP shocks, $\Delta Credit_{i,t}$ and $\Delta BankCredit_{i,t}$ are yoy growth rates of total credit to non-financial private sector relative to GDP and of bank credit to non-financial private sector, respectively. $\Delta GDP_{i,t}$ is the yoy real GDP growth, $\Delta ER_{i,t}$ is the year-on-year local currency appreciation rate against USD. Bank-specific controls are i) the ratio of net income to total assets, ii) growth in total loans, iii) the Tier 1 Core Capital ratio, and iv) the ratio of liquid assets to total assets. Columns (1) and (3) (Columns (2) and (4)) show results for banks that in a given year are in the bottom 50 % (top 50%) of banks in a given country according to the share of residential loans in total loans.

A.3 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:

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

where $Ma\tilde{P}P_{i,t}^j$ 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. In the baseline specification, 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 the 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:

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

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 Tables A4-A6 present results for the specification (A.1) for the $Ma\tilde{P}P^{BC}$ and $Ma\tilde{P}P^{HH}$ as dependent variables, respectively. Columns (3) and (4) 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 non-financial 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 also control for the domestic financial conditions index, and in the regression for $Ma\tilde{P}P^{BC}$ —for the 3-month money market rate. In columns (5)-(12) we also control for the lagged 3-year moving average of the respective corporate credit riskiness measure, which would later be the dependent variable in the second-stage regression. Additionally, we consider growth rates of real GDP, real house prices, total or bank credit on year-on-year (columns (7)-(10)) or on 2-year basis (columns (11)-(12)) instead of the quarterly basis. Given the reduced number of observations when controlling for the moving average of the corporate credit riskiness measures and other variables, we choose (A.1) as our preferred specification.

The results remain broadly unchanged when using MaPP shocks derived via specifications in columns (3)-(12), as shown in Tables A7-A9. For the TDTA and TDtE measures of corporate credit riskiness, the interaction terms of household-specific MaPP shocks with the credit to GDP growth are always positive and statistically significant, while for the ICR measure the coefficients of the interaction term are always positive but statistically significant in 2 out of 5 alternative specifications.

Table (A4) *Macroeprudential shocks: first-stage regressions for the TDTA riskiness measure*

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$M\tilde{a}P^{BC}$	$M\tilde{a}P^{HH}$	$M\tilde{a}P^{BC}$	$M\tilde{a}P^{HH}$	$M\tilde{a}P^{BC}$	$M\tilde{a}P^{HH}$	$M\tilde{a}P^{BC}$	$M\tilde{a}P^{HH}$	$M\tilde{a}P^{BC}$	$M\tilde{a}P^{HH}$	$M\tilde{a}P^{BC}$	$M\tilde{a}P^{HH}$
GDP^f	0.142* (0.085)	0.156** (0.064)	0.250* (0.144)	0.082 (0.090)	0.020 (0.201)	0.312** (0.125)	0.043 (0.208)	0.359*** (0.130)	0.094 (0.223)	0.320** (0.133)	0.081 (0.223)	0.393*** (0.140)
$\Delta GDP_{i,t-1}$	-2.434 (2.899)	-0.504 (2.086)	-1.763 (4.756)	-2.909 (2.581)	7.734 (6.986)	2.954 (3.970)	6.981 (7.146)	3.030 (4.005)	5.883 (7.532)	-0.220 (4.077)	-0.220 (4.077)	
$\Delta_y Credit_{i,t-1}$	-1.572 (2.212)	1.137 (1.678)			-13.362*** (5.157)	3.592 (3.912)						
$\Delta_y ER_{i,t-1}$	-1.407 (1.908)	-1.775 (1.393)	-2.864 (2.576)	-1.216 (1.673)	-9.842*** (3.207)	-1.280 (2.108)	-6.673*** (3.152)	-0.169 (2.199)	-7.783** (3.273)	-1.221 (2.100)	-6.406** (3.186)	-0.449 (2.139)
$CAOpen_{t-4}$	0.139 (0.170)	0.022 (0.112)	0.142 (0.261)	0.088 (0.145)	-0.118 (0.311)	-0.058 (0.168)	-0.107 (0.313)	0.014 (0.177)	0.048 (0.333)	-0.060 (0.175)	-0.127 (0.311)	0.067 (0.183)
FDI_{t-4}	-0.581 (1.622)	-2.397** (1.104)	-0.054 (2.187)	-4.183*** (1.486)	-4.890 (3.421)	-1.278 (1.986)	-4.591 (3.327)	-1.645 (2.027)	-4.615 (3.386)	-0.385 (2.075)	-4.441 (3.354)	-1.789 (2.070)
$\Delta_y HPI_{i,t-1}$	1.382 (2.376)	0.994 (1.802)	-0.306 (3.551)	1.596 (2.268)	3.402 (5.438)	-5.543 (3.416)						
$\Delta_y BankCredit_{i,t-1}$			5.010* (2.571)	0.635 (1.633)								
$\Delta_y NFCBonds_{i,t-1}$			-0.197 (0.399)									
$nominalrate_{i,t-1}$			-0.032 (0.064)									
$FCI_{i,t-1}$				-0.353*** (0.132)								
$TDTA_{i,t-1}^{m2}$					0.228 (0.231)	-0.207 (0.154)	0.131 (0.232)	-0.250 (0.161)	0.208 (0.249)	-0.120 (0.168)	0.117 (0.247)	-0.349** (0.174)
$\Delta Credit_{i,t-1}$							2.592 (2.359)	5.522*** (1.661)				
$\Delta HPI_{i,t-1}$							1.471 (1.940)	-3.425** (1.392)	1.021 (2.053)	-3.160** (1.378)		
$\Delta Credit_{i,t-1}^{NFC}$									0.792 (1.911)			
$\Delta Credit_{i,t-1}^{HH}$									2.923*** (0.874)			
$\Delta_y GDP_{i,t-1}$										5.787 (5.261)	5.173 (3.181)	
$\Delta_y Credit_{i,t-1}$										1.317 (1.537)	4.325*** (1.113)	
$\Delta_y HPI_{i,t-1}$										-0.579 (1.512)	-2.956*** (0.944)	
Observations	2,861	2,861	1,718	1,914	1,063	1,063	1,051	1,051	992	1,027	1,033	1,033
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. For all variables, Δ_y , Δ and Δ_{2y} denote growth rates on quarter-on-quarter, year-on-year, and on 2-year basis, respectively. Additional variables not mentioned in the main text: GDP^f is the one-year ahead GDP forecasts from Consensus Forecasts, $CAOpen$ is the Chinn Ho's Capital Account Index and FDI is the financial development in the domestic private nonfinancial sector, $\Delta_y HPI$ is the real house price growth (quarter-on-quarter, qoq), $\Delta_y BankCredit$ is qoq growth of real bank credit to the domestic private nonfinancial sector, $\Delta_y NFCBonds$ is the qoq growth of the non-financial corporate bonds to GDP ratio, $\Delta Credit_{i,t-1}^{NFC}$ and $\Delta Credit_{i,t-1}^{HH}$ are yoy growth rates of domestic credit to nonfinancial corporates and to households, respectively. $TDTA_{i,t-1}^{m2}$ is the 3-year moving average of the TDTA corporate credit riskiness measure. Finally, $nominalrate$ stands for the 3-month money market rate and FCI for a domestic financial conditions index.

Table (A5) *Macroprudential shocks: first-stage regressions for the TDE riskiness measure*

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	\widetilde{MaPP}^{BC}	\widetilde{MaPP}^{HH}	\widetilde{MaPP}^{BC}	\widetilde{MaPP}^{HH}	\widetilde{MaPP}^{BC}	\widetilde{MaPP}^{HH}	\widetilde{MaPP}^{BC}	\widetilde{MaPP}^{HH}	\widetilde{MaPP}^{BC}	\widetilde{MaPP}^{HH}	\widetilde{MaPP}^{BC}	\widetilde{MaPP}^{HH}
GDP_f	0.142* (0.085)	0.156** (0.064)	0.250* (0.144)	0.082 (0.090)	0.140 (0.212)	0.327** (0.129)	0.095 (0.213)	0.371** (0.133)	0.141 (0.229)	0.321** (0.135)	0.137 (0.231)	0.377*** (0.143)
$\Delta GDP_{i,t-1}$	-2.434 (2.899)	-0.504 (2.086)	-1.763 (4.756)	-2.909 (2.581)	5.454 (7.217)	3.712 (3.992)	6.664 (7.156)	3.500 (4.015)	5.699 (7.476)	-0.000 (4.091)		
$\Delta_q Credit_{i,t-1}$	-1.572 (2.212)	1.137 (1.678)	-22.373*** (6.318)	4.677 (4.035)								
$\Delta_q ER_{i,t-1}$	-1.407 (1.908)	-1.775 (1.393)	-2.864 (2.576)	-1.216 (1.673)	-8.750** (3.397)	-1.510 (2.155)	-5.668* (3.249)	-0.456 (2.272)	-6.639** (3.352)	-1.615 (2.155)	-5.166 (3.289)	-0.659 (2.282)
$CAOpen_{t-4}$	0.139 (0.170)	0.022 (0.112)	0.142 (0.261)	0.088 (0.145)	-0.191 (0.318)	0.004 (0.168)	-0.169 (0.313)	0.085 (0.179)	-0.014 (0.330)	0.010 (0.178)	-0.186 (0.313)	0.151 (0.186)
FDI_{t-4}	-0.581 (1.622)	-2.397** (1.104)	-0.054 (2.187)	-4.183*** (1.486)	-5.148 (3.762)	-0.340 (2.147)	-3.745 (3.489)	-0.613 (2.183)	-3.797 (3.536)	0.373 (2.231)	-3.711 (3.535)	-0.929 (2.222)
$\Delta_q HPI_{i,t-1}$	1.382 (2.376)	0.994 (1.802)	-0.306 (3.551)	1.596 (2.268)	1.349 (6.072)	-4.976 (3.462)						
$\Delta_q BankCredit_{i,t-1}$			5.010* (2.571)	0.635 (1.633)								
$\Delta_q NFCBonds_{i,t-1}$			-0.197 (0.399)									
$nominalrate_{i,t-1}$			-0.032 (0.064)									
$FCI_{i,t-1}$				-0.353*** (0.132)								
$TDE_{i,t-1}^{ma}$					0.153 (0.250)	-0.351** (0.157)	-0.079 (0.247)	-0.402** (0.164)	-0.054 (0.254)	-0.246 (0.168)	-0.087 (0.268)	-0.481*** (0.179)
$\Delta Credit_{i,t-1}$						2.292 (2.491)	2.292 (2.491)	5.881*** (1.703)				
$\Delta HPI_{i,t-1}$						1.289 (2.014)	1.289 (2.014)	-3.001** (1.423)	0.734 (2.155)	-2.834** (1.408)		
$\Delta CreditNFC_{i,t-1}$									0.401 (1.988)	2.899*** (0.876)		
$\Delta CreditHH_{i,t-1}$											5.445 (5.407)	6.124* (3.246)
$\Delta_{2y} GDP_{i,t-1}$											1.357 (1.558)	4.507*** (1.123)
$\Delta_{2y} Credit_{i,t-1}$												-2.555*** (0.966)
$\Delta_{2y} HPI_{i,t-1}$												
Observations	2,861	2,861	1,718	1,914	1,049	1,049	1,037	1,037	978	1,013	1,020	1,020
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Refer to Table A4 for variables descriptions.

Table (A6) *Macroeprudential shocks: first-stage regressions for the ICR riskiness measure*

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	\tilde{MaPP}^{BC}	\tilde{MaPP}^{HH}	\tilde{MaPP}^{BC}	\tilde{MaPP}^{HH}	\tilde{MaPP}^{BC}	\tilde{MaPP}^{HH}	\tilde{MaPP}^{BC}	\tilde{MaPP}^{HH}	\tilde{MaPP}^{BC}	\tilde{MaPP}^{HH}	\tilde{MaPP}^{BC}	\tilde{MaPP}^{HH}
GDP_f	0.14* (0.09)	0.16** (0.06)	0.25* (0.14)	0.08 (0.09)	0.03 (0.20)	0.31** (0.13)	0.05 (0.21)	0.36*** (0.13)	0.09 (0.22)	0.32** (0.13)	0.08 (0.22)	0.40*** (0.14)
$\Delta GDP_{i,t-1}$	-2.43 (2.90)	-0.50 (2.09)	-1.76 (4.76)	-2.91 (2.58)	7.39 (7.01)	3.41 (3.97)	6.93 (7.13)	3.46 (4.00)	5.68 (7.48)	-0.12 (4.10)		
$\Delta_q Credit_{i,t-1}$	-1.57 (2.21)	1.14 (1.68)			-13.17** (5.17)	3.59 (3.91)						
$\Delta_q ER_{i,t-1}$	-1.41 (1.91)	-1.78 (1.39)	-2.86 (2.58)	-1.22 (1.67)	-9.79*** (3.20)	-1.33 (2.12)	-6.60** (3.16)	-0.21 (2.21)	-7.62** (3.29)	-1.21 (2.10)	-6.25** (3.18)	-0.52 (2.21)
$CAOpen_{i,t-4}$	0.14 (0.17)	0.02 (0.11)	0.14 (0.26)	0.09 (0.15)	-0.15 (0.31)	-0.04 (0.17)	-0.14 (0.31)	0.04 (0.18)	0.001 (0.33)	-0.05 (0.17)	-0.15 (0.31)	0.10 (0.18)
$FDI_{i,t-4}$	-0.58 (1.62)	-2.40** (1.10)	-0.05 (2.19)	-4.18*** (1.49)	-4.95 (3.69)	-0.71 (2.11)	-4.23 (3.58)	-1.02 (2.15)	-4.18 (3.61)	-0.43 (2.18)	-4.11 (3.610)	-1.00 (2.19)
$\Delta_q HPI_{i,t-1}$	1.38 (2.38)	0.99 (1.80)	-0.31 (3.55)	1.60 (2.27)	3.53 (5.48)	-5.25 (3.44)						
$\Delta_q BankCredit_{i,t-1}$												
$\Delta_q NFCBonds_{i,t-1}$												
$nominalrate_{i,t-1}$												
$FCI_{i,t-1}$				-0.35*** (0.13)								
$ICR_{i,t-1}^m$					0.13 (0.29)	-0.24 (0.18)	-0.01 (0.29)	-0.27 (0.19)	-0.02 (0.30)	-0.05 (0.20)	-0.02 (0.30)	-0.34* (0.19)
$\Delta Credit_{i,t-1}$							2.84 (2.370)	5.47*** (1.664)				
$\Delta HPI_{i,t-1}$							1.59 (1.94)	-3.29** (1.40)	1.20 (2.05)	-3.18** (1.38)	1.08 (1.91)	
$\Delta CreditNFC_{i,t-1}$												
$\Delta CreditHH_{i,t-1}$										2.93*** (0.88)		
$\Delta_{2y} GDP_{i,t-1}$											6.06 (5.29)	5.27* (3.19)
$\Delta_{2y} Credit_{i,t-1}$											1.54 (1.50)	4.03*** (1.08)
$\Delta_{2y} HPI_{i,t-1}$											-0.46 (1.50)	-2.96*** (0.95)
Observations	2,861	2,861	1,718	1,914	1,063	1,063	1,051	1,051	992	1,027	1,033	1,033
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Refer to Table A4 for variables descriptions.

Table (A7) *Baseline results with macroprudential shocks from alternative first-stage regression specifications*

VARIABLES	(1) TDTA	(2) TDTA	(3) TDTA	(4) TDTA	(5) TDTA
$TDTA_{t-1}$	0.471*** (0.052)	0.512*** (0.034)	0.512*** (0.035)	0.506*** (0.035)	0.509*** (0.035)
$\Delta Credit_{t-1}$	0.013 (0.009)	0.015** (0.007)	0.016** (0.007)	0.017** (0.007)	0.015** (0.007)
ΔGDP_{t-1}	0.053*** (0.013)	0.046*** (0.015)	0.047*** (0.016)	0.048*** (0.017)	0.044** (0.016)
$\Delta_q ER_{t-1}$	-0.018** (0.006)	-0.011* (0.006)	-0.011* (0.006)	-0.010 (0.007)	-0.013** (0.006)
$\bar{\varepsilon}_{i,t-1}^{HH,1}$	-0.002 (0.043)				
$\bar{\varepsilon}_{i,t-1}^{HH,1} \times \Delta Credit_{i,t-1}$	0.014* (0.007)				
$\bar{\varepsilon}_{i,t-1}^{HH,2}$		0.017 (0.025)			
$\bar{\varepsilon}_{i,t-1}^{HH,2} \times \Delta Credit_{i,t-1}$		0.012** (0.005)			
$\bar{\varepsilon}_{i,t-1}^{HH,3}$			0.021 (0.023)		
$\bar{\varepsilon}_{i,t-1}^{HH,3} \times \Delta Credit_{i,t-1}$			0.011* (0.006)		
$\bar{\varepsilon}_{i,t-1}^{HH,4}$				0.017 (0.024)	
$\bar{\varepsilon}_{i,t-1}^{HH,4} \times \Delta Credit_{i,t-1}$				0.011** (0.005)	
$\bar{\varepsilon}_{i,t-1}^{HH,5}$					0.010 (0.024)
$\bar{\varepsilon}_{i,t-1}^{HH,5} \times \Delta Credit_{i,t-1}$					0.014*** (0.005)
Observations	849	989	977	921	959
Number of Nat_Code	18	24	24	23	24
Adjusted R-squared	0.378	0.404	0.397	0.405	0.391
Country FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Refer to Table 6 for variable descriptions. The macroprudential shocks are derived as residuals from regressions in columns (3)-(12) of Table A4: $\bar{\varepsilon}_{t-1}^{HH,1}$ is the household-specific macroprudential policy shock derived from regression in column (3), $\bar{\varepsilon}_{t-1}^{HH,2}$ —in column (5), $\bar{\varepsilon}_{t-1}^{HH,3}$ —in column (7), $\bar{\varepsilon}_{t-1}^{HH,4}$ —in column (9) and $\bar{\varepsilon}_{t-1}^{HH,5}$ —in column (11). The coefficient estimates for broad-based and corporate-specific macroprudential shocks are omitted for simplicity, but they are almost always not statistically significant.

Table (A8) *Baseline results with macroprudential shocks from alternative first-stage regression specifications*

VARIABLES	(1) TDtE	(2) TDtE	(3) TDtE	(4) TDtE	(5) TDtE
$TDtE_{t-1}$	0.358*** (0.043)	0.375*** (0.050)	0.373*** (0.049)	0.379*** (0.051)	0.363*** (0.048)
$\Delta Credit_{t-1}$	0.019* (0.011)	0.027*** (0.005)	0.028*** (0.005)	0.027*** (0.006)	0.027*** (0.005)
ΔGDP_{t-1}	0.062*** (0.019)	0.060*** (0.016)	0.060*** (0.017)	0.061*** (0.018)	0.054*** (0.016)
$\Delta_q ER_{t-1}$	-0.001 (0.007)	0.006 (0.008)	0.006 (0.009)	0.007 (0.009)	0.004 (0.009)
$\bar{\varepsilon}_{t-1}^{HH,1}$	-0.118** (0.054)				
$\bar{\varepsilon}_{t-1}^{HH,1} \times \Delta Credit_{t-1}$	0.024** (0.010)				
$\bar{\varepsilon}_{t-1}^{HH,2}$		-0.081 (0.055)			
$\bar{\varepsilon}_{i,t-1}^{HH,2} \times \Delta Credit_{i,t-1}$		0.021** (0.009)			
$\bar{\varepsilon}_{i,t-1}^{HH,3}$			-0.078 (0.053)		
$\bar{\varepsilon}_{i,t-1}^{HH,3} \times \Delta Credit_{i,t-1}$			0.019** (0.009)		
$\bar{\varepsilon}_{i,t-1}^{HH,4}$				-0.080 (0.053)	
$\bar{\varepsilon}_{i,t-1}^{HH,4} \times \Delta Credit_{i,t-1}$				0.023** (0.008)	
$\bar{\varepsilon}_{i,t-1}^{HH,5}$					-0.103* (0.052)
$\bar{\varepsilon}_{i,t-1}^{HH,5} \times \Delta Credit_{i,t-1}$					0.026*** (0.009)
Observations	841	975	963	907	946
Number of Countries	18	24	24	23	24
Adjusted R-squared	0.249	0.236	0.229	0.240	0.206
Country FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Refer to Table 6 for variable descriptions. The macroprudential shocks are derived as residuals from regressions in columns (3)-(12) of Table A5: $\bar{\varepsilon}_{t-1}^{HH,1}$ is the household-specific macroprudential policy shock derived from regression in column (3), $\bar{\varepsilon}_{t-1}^{HH,2}$ -in column (5), $\bar{\varepsilon}_{t-1}^{HH,3}$ -in column (7), $\bar{\varepsilon}_{t-1}^{HH,4}$ -in column (9) and $\bar{\varepsilon}_{t-1}^{HH,5}$ -in column (11). The coefficient estimates for broad-based and corporate-specific macroprudential shocks are omitted for simplicity, but they are almost always not statistically significant.

Table (A9) *Baseline results with macroprudential shocks from alternative first-stage regression specifications*

VARIABLES	(1) ICR	(2) ICR	(3) ICR	(4) ICR	(5) ICR
ICR_{t-1}	0.313*** (0.052)	0.263*** (0.073)	0.264*** (0.074)	0.259*** (0.080)	0.261*** (0.074)
$\Delta Credit_{t-1}$	0.008 (0.011)	0.020*** (0.005)	0.022*** (0.005)	0.021*** (0.006)	0.019*** (0.005)
ΔGDP_{t-1}	0.032** (0.015)	0.033** (0.013)	0.036** (0.015)	0.038** (0.015)	0.030** (0.013)
$\Delta_q ER_{i,t-1}$	0.002 (0.006)	0.005 (0.007)	0.007 (0.007)	0.008 (0.007)	0.006 (0.008)
$\bar{\varepsilon}_{i,t-1}^{HH,1}$	-0.091* (0.046)				
$\bar{\varepsilon}_{i,t-1}^{HH,1} \times \Delta Credit_{i,t-1}$	0.018* (0.010)				
$\bar{\varepsilon}_{i,t-1}^{HH,2}$		-0.033 (0.052)			
$\bar{\varepsilon}_{i,t-1}^{HH,2} \times \Delta Credit_{i,t-1}$		0.009 (0.008)			
$\bar{\varepsilon}_{i,t-1}^{HH,3}$			-0.034 (0.046)		
$\bar{\varepsilon}_{i,t-1}^{HH,3} \times \Delta Credit_{i,t-1}$			0.008 (0.007)		
$\bar{\varepsilon}_{i,t-1}^{HH,4}$				-0.045 (0.047)	
$\bar{\varepsilon}_{i,t-1}^{HH,4} \times \Delta Credit_{i,t-1}$				0.014* (0.007)	
$\bar{\varepsilon}_{i,t-1}^{HH,5}$					-0.047 (0.047)
$\bar{\varepsilon}_{i,t-1}^{HH,5} \times \Delta Credit_{i,t-1}$					0.012 (0.008)
Observations	849	989	977	921	959
Number of Nat_Code	18	24	24	23	24
Adjusted R-squared	0.191	0.121	0.121	0.128	0.105
Country FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Refer to Table 6 for variable descriptions. The macroprudential shocks are derived as residuals from regressions in columns (3)-(12) of Table A6: $\bar{\varepsilon}_{t-1}^{HH,1}$ is the household-specific macroprudential policy shock derived from regression in column (3), $\bar{\varepsilon}_{t-1}^{HH,2}$ —in column (5), $\bar{\varepsilon}_{t-1}^{HH,3}$ —in column (7), $\bar{\varepsilon}_{t-1}^{HH,4}$ —in column (9) and $\bar{\varepsilon}_{t-1}^{HH,5}$ —in column (11). The coefficient estimates for broad-based and corporate-specific macroprudential shocks are omitted for simplicity, but they are almost always not statistically significant.

A.4 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 A10 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 when credit growth has been rapid in the recent past.

Table (A10) *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
$\bar{\varepsilon}_{i,t-1}^{HH}$	0.057 (0.064)	0.049 (0.062)	0.071 (0.046)	0.067 (0.052)
$\bar{\varepsilon}_{i,t-1}^{HH} \times \Delta HHCredit_{i,t-1}$	-0.031** (0.013)	-0.031** (0.013)	-0.078*** (0.013)	-0.077*** (0.012)
$nominalrate_{i,t-1}$		-0.135*** (0.046)		-0.244*** (0.068)
$\Delta_q HPI_{i,t-1}$	0.318*** (0.065)	0.308*** (0.066)		
$\Delta_q HHCredit_{i,t-1}$	0.054*** (0.009)	0.050*** (0.009)	0.125*** (0.026)	0.116*** (0.024)
$\Delta GDP_{i,t-1}$	0.162*** (0.045)	0.135*** (0.046)	0.063 (0.084)	0.009 (0.060)
$\Delta_q ER_{i,t-1}$	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 Countries	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.

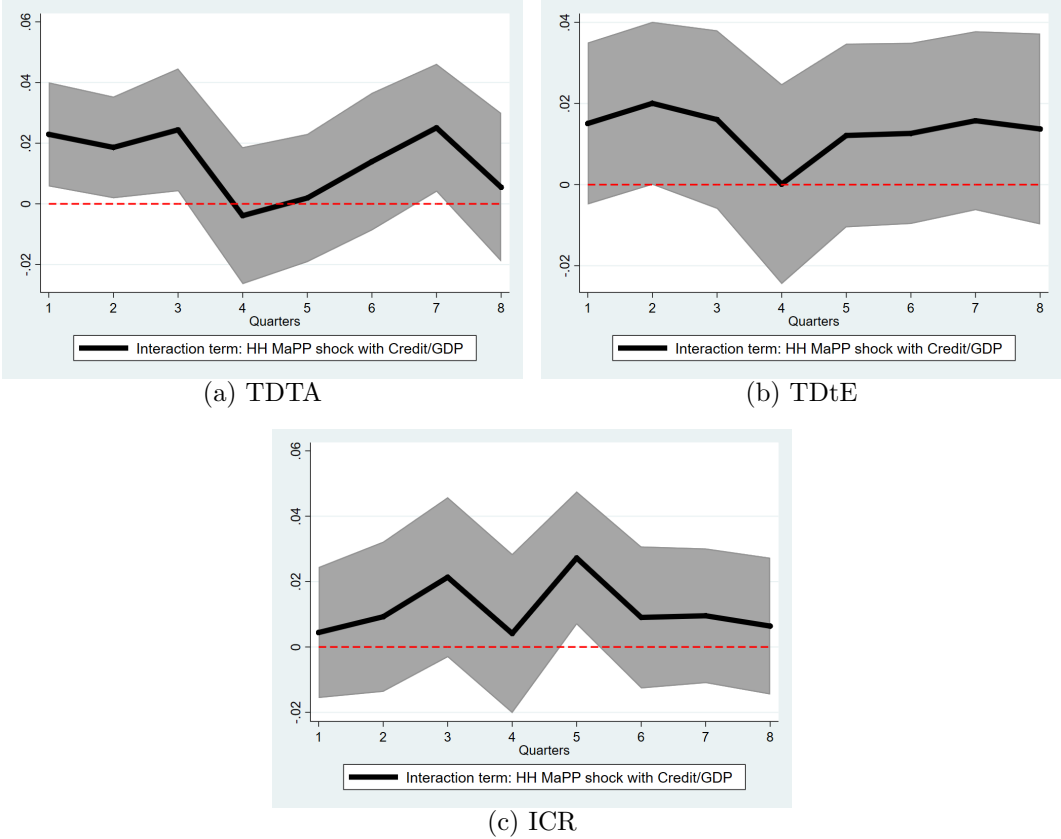
A.5 Deriving impact of macroprudential policies on corporate credit riskiness using local projections

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 ???. Figure 6 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 (6) *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.6 Results with MaPP actions

The results are robust to using macroprudential policy actions rather than shocks. We replace the MaPP shocks in (3) and (4), with changes in policy actions using $MaPP^{HH(BC)}$ and their four-period sums ($MaPP_{sum}^{HH(BC)}$) respectively. Table A11 below present the results for the baseline specifications.

Table (A11) *Baseline results using MaPP actions*

VARIABLES	(1) TDTA	(2) ICR	(3) TDtE	(4) TDTA	(5) ICR	(6) TDtE
<i>DependentVariable</i> _{<i>i,t-1</i>}	0.529*** (0.042)	0.354*** (0.035)	0.406*** (0.035)	0.529*** (0.042)	0.349*** (0.034)	0.402*** (0.035)
<i>MaPP</i> ^{HH} _{<i>i,t-1</i>}	0.005 (0.041)	-0.064 (0.043)	-0.078* (0.042)			
<i>MaPP</i> ^{HH} _{<i>i,t-2</i>}	0.114** (0.048)	0.004 (0.042)	-0.023 (0.054)			
<i>MaPP</i> ^{HH} _{<i>i,t-3</i>}	0.080 (0.047)	0.003 (0.067)	-0.012 (0.058)			
<i>MaPP</i> ^{HH} _{<i>i,t-4</i>}	-0.003 (0.043)	0.067* (0.037)	0.056 (0.049)			
Δ <i>Credit</i> _{<i>i,t-1</i>}	0.022*** (0.005)	0.017*** (0.005)	0.024*** (0.005)	0.022*** (0.005)	0.017*** (0.005)	0.023*** (0.004)
Δ <i>GDP</i> _{<i>i,t-1</i>}	0.015 (0.018)	0.015 (0.012)	0.032* (0.016)	0.013 (0.018)	0.012 (0.013)	0.029* (0.016)
Δ _{<i>q</i>} <i>ER</i> _{<i>i,t-1</i>}	-0.013*** (0.004)	0.010* (0.005)	0.005 (0.005)	-0.013*** (0.004)	0.009* (0.005)	0.004 (0.005)
<i>MaPP</i> ^{HH,sum} _{<i>i,t-1</i>}				0.042** (0.020)	-0.021 (0.027)	-0.048 (0.034)
<i>MaPP</i> ^{BC,sum} _{<i>i,t-1</i>}				-0.023 (0.056)	0.009 (0.051)	0.028 (0.052)
<i>MaPP</i> ^{HH,sum} _{<i>i,t-1</i>} × Δ <i>Credit</i> _{<i>i,t-1</i>}				0.005 (0.005)	0.012** (0.005)	0.014*** (0.005)
<i>MaPP</i> ^{BC,sum} _{<i>i,t-1</i>} × Δ <i>Credit</i> _{<i>i,t-1</i>}				-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*^{HH(BC)sum} is the sum of policy actions in the past four quarters.

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