ONLINE APPENDIX

From banks to nonbanks: macroprudential and monetary policy effects on corporate lending

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Appendix A describes the data and presents descriptive statistics. Appendix B includes tables related to the robustness checks discussed in the main text. Appendix C proposes an IV regression to deal with possible endogeneity in the relationship between the nonbank loan share and syndicate composition. Appendix D presents aggregate evidence on bank lending to nonbank borrowers using country-level BIS data. Appendix E presents additional robustness checks discussed in Section 6 of the main paper.

Appendix A: Data

Syndicated loans

We source global corporate syndicated loans from Dealogic, covering nearly all loans issued worldwide in the primary market by nonfinancial firms. We classify banks based on Dealogic SIC codes starting with 60, corresponding to depository institutions. Nonbanks are identified using SIC codes 61 to 67, excluding real estate companies (most SIC codes starting with 65) and certain mortgage brokers (code 6162).[1] For lenders without assigned SIC codes, we apply text-based classification methods, identifying banks by searching for

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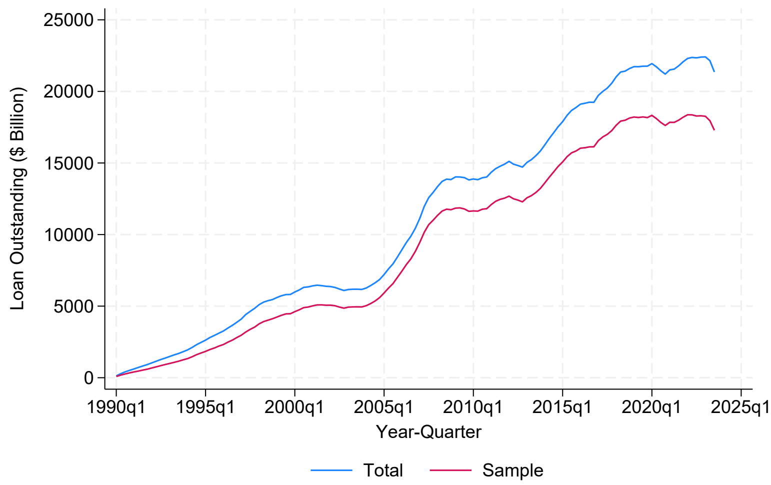
[1]We allocate the following codes starting in 65 to nonbanks: 6510 (Real Estate Operators & Lessors, 6519 (Lessors of Real Property) and 6532 (Real Estate Dealers).

terms such as 'bank,' 'banco,' 'banca,' and 'banque' in their names. A similar approach is used to identify investment banks by detecting the term 'investment.' As is standard in such datasets, we drop international financial institutions, such as the World Bank. Our sample of nonbanks mainly consists of investment banks, broker-dealers, investment funds, and finance companies, but also includes insurance companies, pension funds, private equity firms, venture capital firms, and hedge funds.

Our final sample spans 2000Q1–2019Q4, covering 6,149 lenders, of which 48 percent are nonbanks, in 22 countries (20 AEs and 2 EMDEs). On the borrower side, we restrict the analysis to nonfinancial firms by excluding financial firms—banks, diversified financials, and insurance firms—resulting in a sample of 49,971 unique nonfinancial firms in 156 borrower countries (45 AEs and 111 EMDEs).

Figure A.1: Loan amount outstanding: raw data versus sample



Notes: The blue line is the loan amount outstanding in the full Dealogic dataset, and the red line is the loan amount outstanding in our estimation sample.

Nonfinancial firms' and banks' balance sheets

We source quarterly balance sheet data on nonfinancial firms from S&P Compustat North America and Compustat Global. We clean the data and create a common firm identifier between Dealogic and Compustat by adopting a two-step matching procedure based on the fuzzy matching algorithm of Albuquerque and Iyer (2024). First, we match nonfinancial borrowers across these two datasets based on their unique names and ISINs. Second, for the remainder unmatched firms, we employ a fuzzy matching approach by calculating a Levenshtein Distance-based similarity score, ranging from 0 (least similar) to 100 (most similar), based on three borrower attributes, name, country, and industry. To improve accuracy, we normalize the distance by string length (Levenshtein similarity ratio) and set a minimum threshold ratio of 80, followed by manual verification of the matched firms. We identify around 7,200 unique listed nonfinancial firms with Compustat balance sheet information (all private firms in Dealogic are unmatched by definition).

We use the following balance sheet variables: (i) tangible investment, measured as the logarithm of net capital stock (capital expenditures in physical capital, namely property, plant, and equipment); (ii) intangible investment, computed as the sum of Research and Development (R&D) costs and 30 percent of Selling, General, and Administrative (SG&A) expenses, as in Peters and Taylor (2017); (iii) leverage, measured as the logarithm of total real debt (short- and long-term debt); (iv) liquid assets, proxied by current assets—cash and short-term investments, receivables, inventories, and other current assets—net of current liabilities (short-term debt, accounts payable, income taxes payable, and other current liabilities); (v) employment, computed as the logarithm of the total number of employees; and (vi) probability of default (PD) over the next 12 months, a modified version of Merton's distance-to-default model, computed by the National University of Singapore's Credit Research Initiative (NUS-CRI).

We use Fitch Ratings PRO to explore the bank heterogeneity. It provides comprehensive data on banks' balance sheets and income statements across a broad range of countries. We focus on consolidated financial statements, extracting Tier 1 capital ratios, NPLs as a percentage of total loans, and return on assets (ROA), all measured at the parent-bank level. Since Fitch Ratings PRO and Dealogic lack common lender identifiers, we employ a fuzzy matching algorithm based on lender names and countries. To ensure representativeness of the data, we restrict the sample to countries with at least five banks reporting non-missing Tier 1 capital ratios. We match roughly one-third of the banks in Dealogic with balance sheet data (1,056 banks out of 3,086 banks) across 19 countries.

Country-specific monetary policy shocks

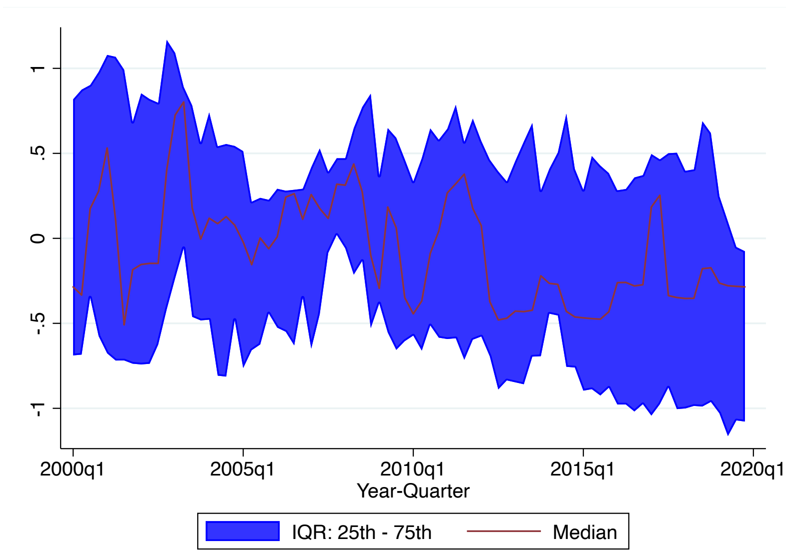
We use MP shocks from Choi et al. (2024), who compile shocks for 176 countries based on a hierarchical identification approach (Table A.1). We restrict the sample to 22 countries whose MP shocks are identified (i) by external sources using a high-frequency identification methodology, or (ii) based on central bank forecast deviations, à la Romer and Romer (2004). We use the cumulative sum of the shocks as our dependent variable is in level terms, as in Elliott et al. (2024, forthcoming), and Cucic and Gorea (2026). Our shock series is roughly balanced between tightening and loosening episodes (Figure A.2).

Table A.1: Sources of monetary policy shocks

Country	Identification	Source	Start Date	End Date
United States	High-Frequency	Jarocinski and Karadi (2020)	1990Q1	2024Q1
Euro Area (14 countries)	High-Frequency	Jarocinski and Karadi (2020)	1999Q1	2023Q4
United Kingdom	High-Frequency	Cesa-Bianchi et al. (2020)	1997Q1	2015Q4
Sweden	High-Frequency	Amberg et al. (2022)	1999Q1	2018Q4
Japan	High-Frequency	Kubota and Shintani (2022)	1992Q1	2020Q4
India	High-Frequency	Lakdawala and Sengupta (2021)	2003Q1	2020Q4
Canada	CBFD (a la R&R 2004)	Champagne and Sekkel (2018)	1974Q1	2015Q4
Brazil	CBFD (a la R&R 2004)	Alberola et al. (2021)	1974Q1	2015Q4
Norway	CBFD (a la R&R 2004)	Holm et al. (2021)	1990Q1	2018Q4

Notes: CBFD refers to Central Bank Forecasts Deviations.

Figure A.2: Monetary policy shocks over time

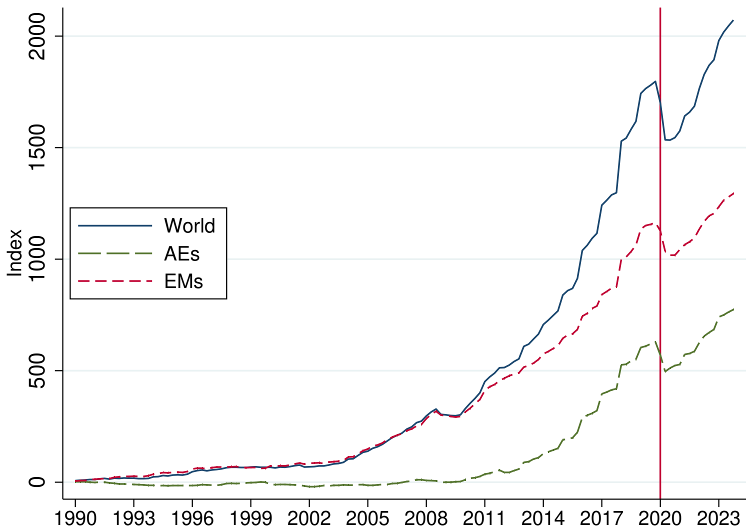


Notes: Red line is the median sample values of the MP shocks, and the blue area indicates the interquartile range.

Country-specific macroprudential policy shocks

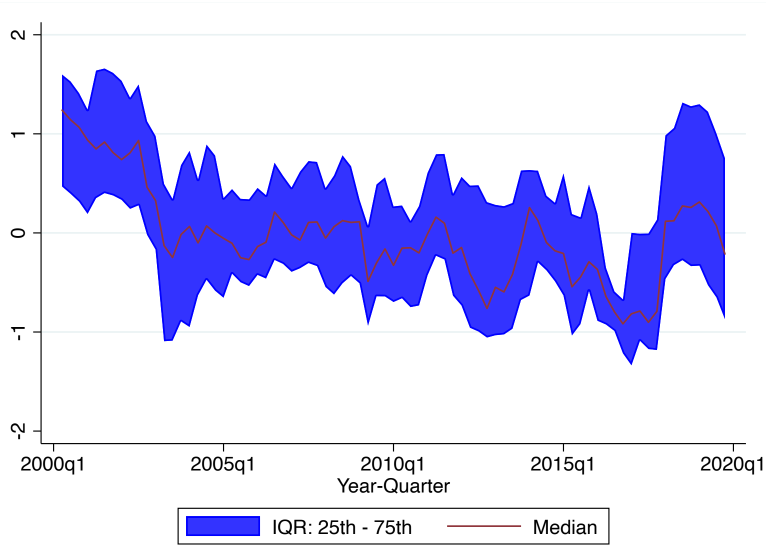
We compute our MaPP shocks as described in Section 2 of the main paper. We find that the MaPP shocks are able to reproduce stylized responses from the literature (Araujo et al. 2024). A one-standard deviation contractionary MaPP shock makes the banking sector more resilient to shocks, depicted by an improvement in banks' financial health, but GDP growth, private credit growth, and bank stock prices fall (Figure A.6).

Figure A.3: Net cumulative sum of macroprudential actions



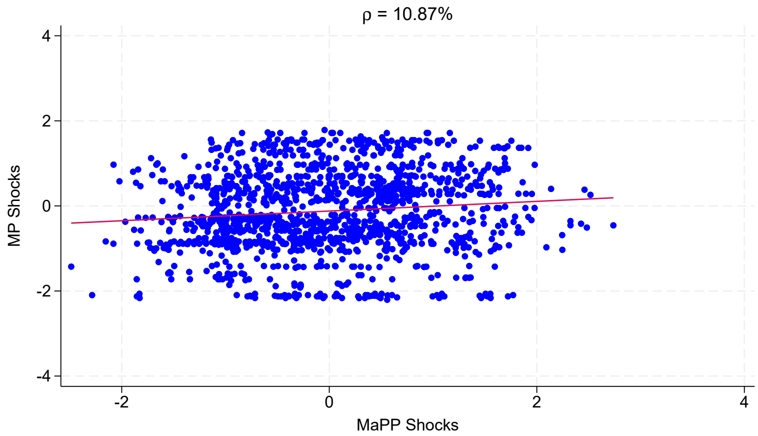
Notes: Alam et al. (2025) iMaPP database and authors' calculations. The red vertical line marks the start of the Covid-19 pandemic in 2020Q1.

Figure A.4: MaPP shocks over time



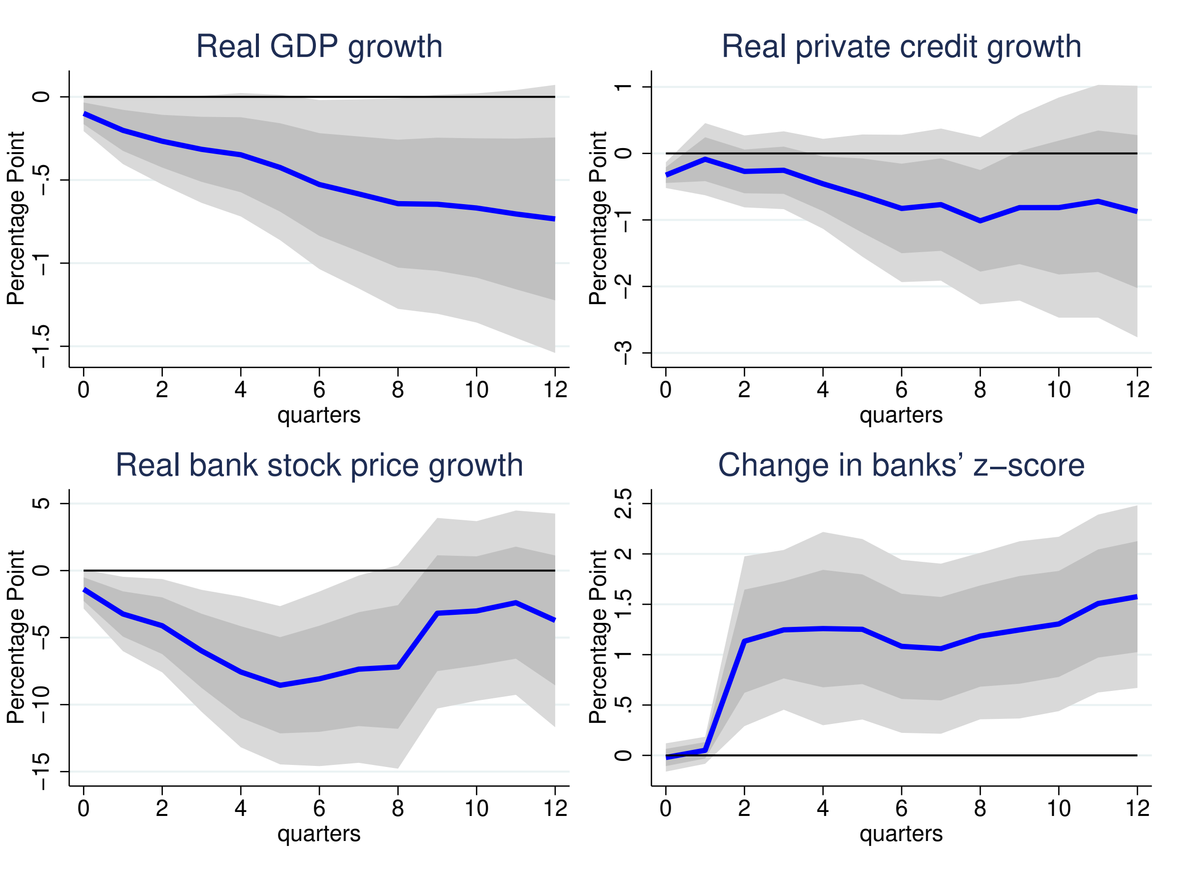
Notes: Red line is the median sample values of the MaPP shocks, and the blue area indicates the interquartile range.

Figure A.5: Correlation of MP and MaPP shocks



Notes: Red line is the linear regression line between the two series.

Figure A.6: Country-level responses to MaPP shocks



Notes: Cumulative impulse responses over 12 quarters following a one-standard deviation increase in MaPP shocks. Blue line is the point estimate, and dark (light) grey areas refer to the associated 68% (90%) confidence bands. Standard errors clustered by country.

Appendix B: Additional tables

Table B.1: Asymmetric effects

	(1) Loans	(2) Loans	(3) Loans	(4) Loans
MP^{+} Shock	-0.081***	-0.022***	-0.023***	-0.023***
	(0.005)	(0.004)	(0.003)	(0.003)
MP^{-} Shock	0.061***	0.019***	0.022***	0.019***
	(0.005)	(0.004)	(0.003)	(0.003)
$MaPP^{+}$ Shock	-0.041***	-0.018***	-0.020***	-0.019***
	(0.006)	(0.004)	(0.004)	(0.003)
$MaPP^{-}$ Shock	0.024***	0.021***	0.019***	0.019***
	(0.005)	(0.004)	(0.004)	(0.003)
MP^{+} Shock × Nonbank		0.052***	0.055***	0.045***
		(0.005)	(0.004)	(0.004)
MP^{-} Shock × Nonbank		-0.058***	-0.058***	-0.047***
		(0.005)	(0.004)	(0.004)
$MaPP^{+}$ Shock × Nonbank		0.005	0.006	0.010**
		(0.006)	(0.005)	(0.005)
$MaPP^{-}$ Shock × Nonbank		-0.024***	-0.026***	-0.022***
		(0.006)	(0.005)	(0.004)
Firm FE	✓	✓	✓	
Lender FE	✓	✓	✓	✓
Country × Sector × Time FE		✓		
ILST FE			✓	
Firm × Time FE				✓
Observations	756,483	749,581	748,405	739,818
R^2	0.689	0.727	0.795	0.877

Notes: Dependent variable is the log of new syndicated loans. Standard errors clustered by firm. Asterisks, *, **, and ***, denote statistical significance at the 10%, 5%, and 1% levels.

Table B.2: Risky borrowers

	(1) 5y avg.	(2) Lev. Loans	(3) High PD	(4) Junk rtg.
MP shock	-0.030***	-0.031***	-0.018***	-0.038***
	(0.004)	(0.004)	(0.006)	(0.008)
MaPP shock	-0.019***	-0.020***	-0.018***	-0.019***
	(0.003)	(0.003)	(0.004)	(0.006)
MP shock × Nonbank	0.062***	0.059***	0.076***	0.074***
	(0.005)	(0.007)	(0.008)	(0.012)
MaPP shock × Nonbank	0.023***	0.037***	0.009	0.013
	(0.004)	(0.005)	(0.006)	(0.009)
Nonbank × Risky	-0.008	-0.023***	0.025*	-0.029**
	(0.009)	(0.007)	(0.015)	(0.014)
MP shock × Risky	0.005	0.005	-0.014	0.005
	(0.008)	(0.005)	(0.013)	(0.011)
MaPP shock × Risky	-0.003	0.001	0.002	0.000
	(0.006)	(0.004)	(0.009)	(0.008)
MP shock × Nonbank × Risky	0.002	0.001	-0.011	-0.018
	(0.010)	(0.009)	(0.017)	(0.016)
MaPP shock × Nonbank × Risky	-0.009	-0.025***	0.009	-0.004
	(0.008)	(0.007)	(0.014)	(0.012)
Lender FE	✓	✓	✓	✓
Firm × Time FE	✓	✓	✓	✓
Observations	331,080	331,080	148,648	97,507
R^2	0.819	0.819	0.871	0.804

Notes: Dependent variable is the log of new syndicated loans. Risky is a dummy variable taking the value of one for Risky borrowers. Each column refers to alternative proxies for Risky borrowers: *5y avg.* refers to borrowers with an average loan spread over the past five years in the top quartile of the sample distribution in each quarter; *Lev. loans* refers to leveraged loans; *High PD* captures high-PD borrowers, i.e., firms with a PD in the top quartile of the country-time distribution; *Junk rtg.* refers to borrowers with a credit rating below BBB^-. Standard errors clustered by firm. Asterisks, *, **, and ***, denote statistical significance at the 10%, 5%, and 1% levels.

Table B.3: Real effects

	(1) Total Debt	(2) Liquid assets	(3) Capital exp.	(4) Intangibles	(5) Employment	(6) PD
MP shock	0.049	0.021	0.006	0.033	-0.015	0.012
	(0.031)	(0.044)	(0.016)	(0.022)	(0.020)	(0.057)
MaPP shock	-0.013	-0.040	-0.019	-0.011	-0.024	0.018
	(0.022)	(0.028)	(0.012)	(0.016)	(0.015)	(0.034)
	0.012	-0.046**	0.016**	-0.007	0.017***	0.041*
	(0.014)	(0.020)	(0.008)	(0.011)	(0.007)	(0.023)
MP shock ×	-0.031	-0.013	0.031**	-0.005	0.034***	0.052
	(0.024)	(0.031)	(0.012)	(0.017)	(0.012)	(0.036)
MaPP shock ×	0.013	0.046**	0.019**	0.024*	0.015*	0.003
	(0.017)	(0.022)	(0.008)	(0.013)	(0.008)	(0.022)
Firm controls	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Country × Sector × Time FE	✓	✓	✓	✓	✓	✓
Observations	22,155	16,279	22,779	13,152	21,451	18,024
R^2	0.957	0.926	0.989	0.975	0.990	0.640

Notes: Data are aggregated at the firm-quarter level. The dependent variables are: (1) log of total real debt, (2) log of real net liquid assets, (3) log of real tangible capital expenditures, (4) log of real intangible investment, (5) log of employment, and (6) the probability of default over the next 12 months. *NB relation* dummy equals one if the firm borrowed from a nonbank in the syndicate loan market in the past two years, and zero otherwise. Firm controls refer to the lagged log of total real assets, the debt-to-asset ratio, and the net-liquid-asset ratio. Standard errors clustered by firm. Asterisks, *, **, and ***, denote statistical significance at the 10%, 5%, and 1% levels.

Appendix C: Credit migration to nonbanks: IV

A key empirical challenge in Equation (5) of the main paper is that the nonbank share of a syndicated loan and the syndicate's exposure to weakly capitalized banks may be jointly determined at syndicate formation, reflecting persistent borrower traits or endogenous lender–borrower matching. Borrowers that systematically rely on weaker banks may differ along unobserved dimensions that also shape nonbank participation.

To address this concern, we implement an instrumental-variable strategy, akin to a Bartik-type design, exploiting predetermined variation in banks' balance-sheet strength while avoiding conditioning on realized syndicate composition. We construct a deal-level instrument by interacting predetermined bank-level lending weights (the *share*) with banks' capital ratios (the *shift)*, both measured prior to deal formation and before the realization of MP and MaPP shocks. The *weak bank exposure* instrument is as follows:

$$\textit{Weak bank exposure}_{d,t} = \sum_{b \in \mathcal{B}_d} w_{b,d}^{\text{pre}} \times \textit{Low capital}_{b,t-1} \tag{C.1}$$

where $\mathcal{B}_d$ denotes the set of banks in deal d, and $w_{b,d}^{\text{pre}} = \frac{\sum_{\tau<d} Loan_{b,\tau}}{\sum_{\tau<d} Loan_{\tau}}$ is a predetermined weight equal to bank b's share of aggregate syndicated lending prior to deal d. The numerator is the cumulative volume of loans originated by bank b before deal d, while the denominator is the cumulative volume of all syndicated loans originated by all banks in the sample before deal d. Hence, $w_{b,d}^{\text{pre}}$ measures pre-deal market share and is predetermined at deal formation. We adopt this approach because our sample does not include a clean pre-sample period from which bank-level loan shares could be estimated. For each bank b, $\textit{Low capital}_{b,t-1}$ is an indicator equal to one if the bank's lagged Tier 1 capital ratio falls in the first quartile of the sample distribution at time t-1. Because both the weak capital dummy and the participation weights are determined prior to deal formation, the resulting instrument isolates variation in weak-bank exposure that is plausibly orthogonal to unobserved borrower-level credit demand or deal-specific matching.

We use this computed *weak bank exposure*, along with its interactions with MP and MaPP shocks, as instruments for syndicates with the prevalence of participating banks with weaker capital (our endogenous variable) and the corresponding interaction terms in the second stage. The general expression of the first-stage regression is given by:

$$\begin{aligned} \textit{Weak bank}_{d,t-1} = {} & \pi_1 MP_{d,t-1} + \pi_2 MaPP_{d,t-1} \\ & + \pi_3 \, \textit{Weak bank exposure}_{d,t-1} + \alpha_i + \text{ILST FE} + \epsilon_{d,t} \end{aligned} \tag{C.2}$$

where interactions of $\textit{Weak bank}_{d,t-1}$ with MP and MaPP shocks are instrumented using the corresponding interactions with $\textit{Weak bank exposure}_{d,t-1}$. Given the persistence of bank–borrower relationships, geographic specialization in syndicated lending, and slow-moving bank capitalization, destinations historically more exposed to banks that are weakly capitalized today are more likely to have such banks appear in subsequent syndicates. This monotonic mapping implies a positive first-stage relationship ($\pi_3 > 0$) between predetermined weak-bank exposure and the indicator for weak-bank participation.

Table C.1 shows the general (linear) first-stage regression. It shows that the first-stage coefficient on the instrument is indeed positive, and highly statistically significant. In addition, we assess the relevance and strength of the instruments with the Cragg–Donald F-statistic test for weak identification, and with the Kleibergen–Paap F-test, a version of that test that is robust to heteroskedasticity. The first-stage regression is strong with F-tests that are above conventional critical values.

Table C.1: Nonbank share and bank characteristics: first-stage regression

	(1)
Weak exposure instrument	2.944***
	(0.270)
MP shock	-0.013
	(0.015)
MaPP shock	-0.033***
	(0.010)
Firm FE	✓
ILST FE	✓
Observations	41,441
Cragg–Donald F-test	47.474
Kleibergen-Paap F-test	10.857

Notes: Data aggregated at the syndicated loan deal level. The dependent variable is a dummy variable capturing syndicates with weaker banks (as defined in the main paper). The Cragg–Donald F-test and Kleibergen–Paap F-test assume that under the null, the excluded instruments are not weakly correlated with the endogenous regressors. Standard errors clustered by firm. Asterisks, *, **, and ***, denote statistical significance at the 10%, 5%, and 1% levels.

The second-stage regression is as follows:

$$\begin{aligned} NB\ shr_{d,t} &= \beta_1^{IV} MP_{d,t-1} + \beta_2^{IV} MaPP_{d,t-1} \\ &+ \widehat{Weak\ bank}_{d,t-1} \times (\beta_3^{IV} + \beta_4^{IV} MP_{d,t-1} + \beta_5^{IV} MaPP_{d,t-1}) \\ &+ \alpha_i^{IV} + \text{ILST FE}^{IV} + \epsilon_{d,t}^{IV} \end{aligned} \tag{C.3}$$

where in this specification, three instruments, *Weak bank exposure*$_{d,t-1}$ and its interactions with MP and MaPP shocks, are used to instrument three endogenous regressors: realized *Weak bank*$_{d,t-1}$ and its corresponding interaction terms with the policy shocks. The identifying assumption is that, conditional on borrower demand (captured by firm fixed effects and ILST fixed effects), banks' historical lending shares affect the nonbank share of a syndicated loan only through banks' contemporaneous lending capacity, and not through unobserved borrower demand or deal-specific shocks. This approach isolates variation in weak-bank exposure driven by slow-moving and plausibly exogenous bank balance-sheet constraints, rather than by endogenous syndicate formation.

Table C.2: Nonbank share and bank characteristics: second-stage regression

	(1) Baseline	(2) IV
MP shock	0.017**	0.014
	(0.008)	(0.018)
MaPP shock	0.032***	-0.003
	(0.005)	(0.013)
Bank charact.	0.010**	-0.227***
	(0.005)	(0.056)
MP shock × Bank charact.	0.012**	-0.014
	(0.007)	(0.086)
MaPP shock × Bank charact.	0.016***	0.092**
	(0.005)	(0.044)
Firm FE	✓	✓
ILST FE	✓	✓
Observations	42,354	41,441

Notes: Data aggregated at the syndicated loan deal level. The dependent variable is the share of loans from nonbanks in each syndicated loan deal. Column (1) shows the baseline results from column (2) of Table 4 in the main paper. Column (2) shows the results from an IV regression using the instrument constructed as discussed in the text. Standard errors clustered by firm. Asterisks, *, **, and ***, denote statistical significance at the 10%, 5%, and 1% levels.

Table C.2 shows that our main result on the role of MaPP shocks remains robust when we implement the IV specification. In particular, following a contractionary MaPP shock, the nonbank share in syndicated loan deals increases more for syndicates involving weaker banks, consistent with our baseline interpretation that tighter MaPP induces a reallocation of lending toward nonbank participants. The interaction effect associated with MP shocks is negative but statistically insignificant in the IV specification. This suggests that the differential response we document is primarily driven by the MaPP channel, while the evidence for a comparable monetary policy channel is weaker once potential endogeneity is addressed.

Appendix D: Bank claims on NBFIs: country evidence

In Section 5 of the main paper we find that banks increase lending to NBFIs relative to NFCs following MaPP tightening shocks. The question is whether this pattern extends to banks' overall exposures to nonbanks, i.e., beyond the syndicated loan market. According to the BIS Consolidated Banking Statistics (CBS), banks' claims on NBFIs are primarily *loans and deposits*, which accounted for around 60 percent of all reporting banks' foreign claims on NBFIs over 2013Q4–2019Q4. This component includes syndicated loans, bilateral bank loans and reverse repos. Reverse repos are particularly important for broker-dealers (Financial Stability Board 2025). In turn, debt securities, which include bonds, commercial paper, and securitized loan instruments, accounted for roughly 16 percent during the same period. These statistics suggest it is worth investigating if banks increase their *overall exposure* to nonbank borrowers in response to MaPP tightening.

The CBS report the cross-border and local claims of internationally active banking groups on a consolidated basis. Since 2013Q4, the CBS provide data on bank claims by lender country and counterparty sector, distinguishing between NFCs and NBFIs. This allows us to examine, at the aggregate level, how banking groups reallocate their lending portfolios between NFCs and NBFIs in response to MP and MaPP tightening shocks, complementing the analysis in Table 7 of the main paper.

We note several caveats of the CBS data for our research question. First, the sectoral counterparty breakdown (NFCs vs NBFIs) cannot be combined with information on borrower country and the country of the lender: claims are consolidated to the reporting (lender) country, while the counterparty is identified only by sector. As a result, the analysis cannot separately identify NFC or NBFI exposures by borrower country, nor include borrower-country×time fixed effects to control for sector-specific demand at a granular level. Second, the NFC–NBFI sectoral breakdown is available only for a subset of reporting countries (12 countries in our sample)[2] and only from 2013Q4 onward, limiting the panel dimension to at most 25 quarters for some countries. Third, the NFC–NBFI breakdown applies exclusively to cross-border claims; local claims are not available with this sectoral split. Consequently, the CBS analysis captures banks' cross-border exposures by sector, rather than total lending (cross-border plus local), as in Table 7.

Given these considerations, we re-estimate a version of Equation (8) of the main paper with an alternative set of fixed effects:

$$\begin{aligned}\Delta \log(\text{Claims})_{c,j,t} &= \beta_1 MP_{c,t-1} + \beta_2 MaPP_{c,t-1} \\ &+ \textit{NB borrower}_j \times (\beta_3 MP_{c,t-1} + \beta_4 MaPP_{c,t-1}) + \gamma_c + \mu_{j,t} + \epsilon_{c,j,t} \qquad \text{(D.1)}\end{aligned}$$

where the dependent variable is the quarterly log growth of banks' foreign claims (to proxy new credit as in our baseline) of lender country c on counterparty sector j at quarter t. *NB borrower* is a dummy variable taking the value of one for banks' claims on NBFIs, and zero for claims on NFCS. Our preferred specification includes lender-country fixed effects (γ_c) to absorb persistent supply characteristics, and borrower sector×time fixed effects ($\mu_{j,t}$) to control for quarter-specific demand conditions and risk characteristics common to all NFCs or NBFIs globally. This specification absorbs sector-level shifts in credit demand and financial conditions that could otherwise confound the estimated response of bank lending to MP and MaPP shocks. Identification therefore exploits within-period, cross-lender country variation in the relative allocation of credit to NFCs versus NBFIs.

Table D.1 shows that our main finding—a reallocation of lending from NFCs to NBFIs following MaPP tightening shocks—is confirmed using CBS data at the country level. This result is robust to alternative fixed-effect specifications, including lender-country×quarter fixed effects in column (3), which absorb all shocks and characteristics

[2]The U.S., the U.K., Austria, Belgium, Canada, France, Greece, Ireland, Italy, The Netherlands, Spain, and Sweden.

specific to a given lender country in a given quarter, such as funding conditions, balance-sheet constraints, and any global or domestic policy changes affecting total lending. These findings provide tentative evidence that banks increase their exposures to nonbank borrowers while reducing exposures to NFCs in response to MaPP tightening. However, given the limitations discussed previously, these results should be interpreted with caution.

Table D.1: Bank lending to NBFIs and NFCs: BIS consolidated banking statistics

	(1)	(2)	(3)	(4)
MP shock	-0.034	0.243	-	-0.021
	(0.174)	(0.306)		(0.160)
MaPP shock	-0.589**	-0.398	-	-0.413**
	(0.190)	(0.265)		(0.185)
MP shock × NBFI borrower	0.411	0.411	0.411	0.939
	(0.456)	(0.466)	(0.455)	(0.634)
MaPP shock × NBFI borrower	0.977*	0.977*	0.977*	1.008*
	(0.489)	(0.500)	(0.488)	(0.498)
NBFI borrower	1.391**	1.391**	1.391**	-
	(0.527)	(0.539)	(0.526)	
Lender-country FE	✓	✓		✓
Time FE		✓		
Lender-country × Time FE			✓	
Borrower × Time FE				✓
Observations	512	512	512	512
R^2	0.045	0.147	0.535	0.235

Notes: Country-level data from the BIS consolidated banking statistics. Data aggregated at the lender country-counterpart sector-quarter. The dependent variable is the quarterly log growth of banks' claims on each sector (nonbank financial institutions and nonfinancial corporations). Standard errors clustered by lender-country. Asterisks, *, **, and ***, denote statistical significance at the 10%, 5%, and 1% levels.

Appendix E: Extensions and robustness checks

We run a battery of tests and extensions to check the robustness of our main findings mostly related to column (4) of Table 2 of the main paper.

Rescaling coefficients with bank stock prices

The MP and MaPP shocks used in the paper have been standardized to have zero mean and unit standard deviation over the sample. However, their regression coefficients are not necessarily directly comparable. This is because the economic meaning of a one-standard-deviation shock differs across the two policy types. To make their effects more comparable, it is necessary to analyze their impact using a common metric.

While interest rates are a natural metric to assess the stance and transmission of MP, they are unlikely to be suitable for comparing the effects of MaPP shocks. MaPP measures typically operate through regulatory instruments—such as capital buffers or lending restrictions—that do not directly affect policy rates or the yield curve. As a result, using interest rates to compare MP and MaPP effects would underestimate the transmission channels of MaPP.

In contrast, bank stock prices provide a more comprehensive and unified metric: they respond not only to changes in interest rates, but also to shifts in expected future profitability, risk-taking incentives, and regulatory constraints. In this context, bank stock prices serve as a more comparable, and arguably more meaningful, gauge of the market impact of both MP and MaPP shocks. We obtain bank stock price indices for our sample of 22 countries from Refinitiv DataScope. We first regress the log change in real bank stock prices on the MP and MaPP shocks, separately. The estimated coefficient in each regression captures the effect of a one-standard-deviation shock on bank stock prices. We then normalize each shock by its corresponding coefficient, so that the normalized shocks are calibrated to generate a one percent decline in bank stock prices.

Normalizing both shocks in this way allows us to directly compare their relative effects on new lending while holding constant their stock market impact. Re-estimating the preferred specification in column (4) of Table 2 in the main paper using the normalized shocks yields similar conclusions. In particular, the expansion of nonbank lending relative to bank lending is stronger following MP shocks: an MP shock calibrated to reduce bank stock prices by one percent leads to a 5.5 percent relative increase in nonbank lending, compared with a 4.0 percent increase following MaPP shocks (see column 2 of Table E.1). While the difference in magnitudes is smaller than in the baseline specification (column 1), it remains statistically significant at the five percent level. In addition, the normalized shocks also imply a stronger nonbank lending response following MP shocks for U.S. lenders (column 4).

We also show that our results for the U.S. economy remain fully consistent when using the high-frequency identification strategy with sign restrictions proposed by Drechsel and Miura (2026). Their approach isolates high-frequency surprises in bank stock prices around FOMC speeches that focus mainly on bank regulation. These raw surprises are then transformed into 'bank regulation shocks' using sign restrictions that impose a positive comovement between bank stock prices and banks' credit risk. We also normalize these shocks to induce a one percent decline in bank stock prices. We find that bank regulation shocks in column (5) also lead to an expansion in nonbank lending relative to bank lending, consistent with our baseline results.

Table E.1: Rescaling coefficients with bank stock prices, and using Drechsel and Miura (2026) bank regulation shocks

	(1) Baseline	(2) Base: normalized	(3) US baseline	(4) US: normalized	(5) US: bank regulation
MP shock	-0.021***	-0.025***	-	-	-
	(0.002)	(0.003)			
MaPP shock	-0.019***	-0.046***	-	-	-
	(0.002)	(0.004)			
MP shock × Nonbank	0.046***	0.055***	0.128***	0.068***	0.076***
	(0.003)	(0.004)	(0.009)	(0.005)	(0.005)
MaPP shock × Nonbank	0.016***	0.040***	0.028***	0.018***	0.007***
	(0.002)	(0.006)	(0.005)	(0.003)	(0.002)
Lender FE	✓	✓	✓	✓	✓
Firm × Time FE	✓	✓	✓	✓	✓
Observations	739,818	739,818	287,195	287,195	202,117
R^2	0.877	0.877	0.842	0.842	0.852

Notes: Dependent variable is the log of new syndicated loans. Column (1) is the preferred baseline specification, while column (2) is the same specification but shows all coefficients normalized by bank stock prices, such that a one-standard deviation increase in each shock is associated with a one percent decline in bank stock prices. Column (3) is the preferred baseline specification for US lenders only, while column (4) normalizes the coefficients by bank stock prices. Column (5) uses the bank regulation shocks for the U.S. from Drechsel and Miura (2026), with all coefficients normalized by bank stock prices. Standard errors clustered by firm. Asterisks, *, **, and ***, denote statistical significance at the 10%, 5%, and 1% levels.

Nonbank heterogeneity

In the paper we have considered nonbanks as a single group. However, nonbanks vary along several characteristics, including in their funding structures. Following Irani et al.

(2021), we create two groups based on the stability of their liabilities. Specifically, we classify pension funds and insurance companies as nonbanks with stable funding, given the long-term nature of their liabilities, with limited redemption risk. In contrast, we consider investment banks, broker-dealers, finance companies, private equity firms, venture capital firms, and hedge funds to have unstable funding, as their liabilities are typically liquid and subject to withdrawal risk—particularly during periods of financial turbulence.[3]

Table E.2 shows that nonbanks with unstable funding drive our main results during contractionary MP and MaPP shocks. This result further supports the notion that credit migration to the less regulated sector may pose significant financial stability risks, especially when intermediated by nonbanks with unstable funding. These nonbanks are less prone to roll over loans to borrowers during periods of financial stress (Irani et al. 2021, Aldasoro et al. 2025, Chernenko et al. 2025, Fleckenstein et al. 2026).

Table E.2: Funding models of nonbanks

	(1)	(2)	(3)
MP shock	-0.021***	-0.023***	-0.021***
	(0.003)	(0.003)	(0.002)
MaPP shock	-0.020***	-0.020***	-0.019***
	(0.002)	(0.002)	(0.002)
MP shock × Stable Nonbank	-0.117***	-0.105***	-0.090***
	(0.027)	(0.024)	(0.019)
MP shock × Unstable Nonbank	0.058***	0.059***	0.048***
	(0.004)	(0.004)	(0.003)
MaPP shock × Stable Nonbank	-0.048***	-0.031**	-0.017
	(0.018)	(0.015)	(0.013)
MaPP shock × Unstable Nonbank	0.016***	0.018***	0.017***
	(0.003)	(0.003)	(0.002)
Firm FE	✓	✓	
Lender FE	✓	✓	✓
Country × Sector × Time FE	✓		
ILST FE		✓	
Firm × Time FE			✓
Observations	754,557	753,390	744,981
R^2	0.728	0.796	0.878

Notes: Dependent variable is the log of new syndicated loans. *Stable nonbanks* refer to nonbanks with stable funding, namely pension funds and insurance companies. *Unstable nonbanks* are all the other nonbanks. Standard errors clustered by firm. Asterisks, *, **, and ***, denote statistical significance at the 10%, 5%, and 1% levels.

[3] We acknowledge that we are simplifying nonbanks' funding structure as we do not observe their balance sheets, such as the amount of leverage and the maturity of debt.

We explore further the nonbank heterogeneity by breaking down nonbanks into five main types: (i) investment banks and broker-dealers, (ii) business credit institutions, (iii) investment funds and asset managers, (iv) insurance firms and pension funds, and (iv) other nonbanks. When we pool all the nonbank types in column (6) of Table E.3, we find that our main findings are driven by investment banks and broker-dealers. These entities are well-established players in the syndicated loan market, and dominate our sample.

Table E.3: Effect of monetary and macroprudential policy shocks by type of nonbank

	(1)	(2)	(3)	(4)	(5)	(6)
MP shock	-0.022***	-0.021***	-0.022***	-0.021***	-0.021***	-0.022***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
MaPP shock	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
MP shock × Nonbank	-0.048***	0.047***	0.053***	0.048***	0.051***	
	(0.008)	(0.003)	(0.003)	(0.003)	(0.003)	
MaPP shock × Nonbank	-0.018***	0.017***	0.019***	0.017***	0.017***	
	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)	
MP shock × Investment banks, broker-dealers	0.112***					0.063***
	(0.009)					(0.003)
MaPP shock × Investment banks, broker-dealers	0.040***					0.022***
	(0.006)					(0.003)
MP shock × Business credit institution		-0.039***				0.004
		(0.013)				(0.013)
MaPP shock × Business credit institution		-0.032***				-0.021**
		(0.009)				(0.009)
MP shock × Investment funds & asset managers			-0.197***			-0.148***
			(0.016)			(0.016)
MaPP shock × Investment funds & asset managers			-0.042***			-0.024**
			(0.009)			(0.009)
MP shock × Insurance & pension funds				-0.139***		-0.099***
				(0.019)		(0.020)
MaPP shock × Insurance & pension funds				-0.034***		-0.021
				(0.013)		(0.013)
MP shock × Other nonbanks					-0.059***	-0.014
					(0.011)	(0.011)
MaPP shock × Other nonbanks					-0.010	0.005
					(0.008)	(0.008)
Lender FE	✓	✓	✓	✓	✓	✓
Firm × Time FE	✓	✓	✓	✓	✓	✓
Observations	739,818	739,818	739,818	739,818	739,818	739,818
R^2	0.877	0.877	0.877	0.877	0.877	0.877

Notes: Dependent variable is the log of new syndicated loans with exception. Standard errors clustered by firm. Asterisks, *, **, and ***, denote statistical significance at the 10%, 5%, and 1% levels.

By contrast, insurance firms and pension funds, and investment funds and asset managers (including hedge funds, private equity, and other alternative investment vehicles) contract lending in response to MP and MaPP shocks. We conjecture that insurers' and pension funds' lending response following tighter financial conditions driven by the shocks, which may increase corporate credit risk and volatility, thereby raising capital charges and internal risk limits, thus reducing the relative attractiveness of syndicated loans compared with corporate bonds. For investment funds and asset managers, we conjecture that leverage constraints likely limit their capacity to expand lending, as these institutions rely predominantly on investor capital rather than borrowed funds.

Alternative macroprudential shocks

Our baseline MaPP shocks consider MaPP targeting the supply of loans and focused on stress testing, motivated by our research question that focuses on understanding lenders' credit supply behavior following policy shocks. Our set of macroprudential policies is also in the spirit of policies that aim at 'dampening the credit cycle', in the words of Gambacorta and Murcia (2020). They find that tightening these loan-targeted macroprudential policies produces stronger and faster effects on credit growth, whereas capital-based requirements affect credit supply more gradually over the medium term.

In Table E.4 we test the robustness of our results by adding other MaPP tools, and by breaking down our baseline measures into sub-components. Column (2) is very similar to the baseline but only keeps the set of measures that target directly loan supply. Column (3) incorporates reserve requirements to the baseline, while column (4) adds capital requirements, conservation buffers, and countercyclical capital buffers. Overall, our main results are strongly robust to these alternative specifications. Column (4) shows a smaller impact on credit growth when adding capital-based requirements, as these measures tend to be somewhat less effective to curb credit growth in the short run, producing effects over longer horizons (Gambacorta and Murcia 2020).

In turn, columns (5) and (6) breakdown the six baseline MaPP sub-components into two economically distinct groups. Column (5) includes measures that directly constrain credit expansion at the margin, namely limits to credit growth, limits to the loan-to-deposit ratio, and limits to FX loans. Column (6) includes measures that operate primarily through banks' balance-sheet resilience and institutional constraints, namely loan loss provisions, loan restrictions, stress testing, restrictions on profit distribution, and other structural measures. We find that credit leakage to nonbanks remains robust across both groups, although we find a significantly stronger nonbank credit expansion for measures that directly constrain credit expansion.

Table E.4: Alternative MaPP shocks

	(1)	(2)	(3)	(4)	(5)	(6)
MP shock	-0.021***	-0.023***	-0.019***	-0.022***	-0.019***	-0.021***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
MaPP shock	-0.019***	-0.027***	-0.020***	-0.015***	-0.006***	-0.020***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
MP shock × Nonbank	0.046***	0.047***	0.046***	0.047***	0.030***	0.048***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
MaPP shock × Nonbank	0.016***	0.026***	0.016***	0.012***	0.045***	0.015***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Lender FE	✓	✓	✓	✓	✓	✓
Firm × Time FE	✓	✓	✓	✓	✓	✓
Observations	739,818	739,818	739,818	739,818	739,818	739,818
R^2	0.877	0.877	0.877	0.877	0.877	0.877

Notes: Dependent variable is the log of new syndicated loans. Column (1) uses the baseline MaPP shocks described in Section 2 of the main paper; column (2) focuses on measures targeting loan supply; column (3) adds reserve requirements to the baseline; and column (4) adds capital requirements, conservation buffers, and countercyclical capital buffers to the baseline. Column (5) includes measures that directly constrain credit expansion at the margin—namely limits to credit growth, limits to the loan-to-deposit ratio, and limits to FX loans. Column (6) includes measures that operate primarily through banks' balance-sheet resilience and institutional constraints, namely loan loss provisions, loan restrictions, stress testing, restrictions on profit distribution, and other structural measures. Standard errors clustered by firm. Asterisks, *, **, and ***, denote statistical significance at the 10%, 5%, and 1% levels.

We run additional sensitivity checks by: lagging MaPP (and also MP) shocks by two, three, and four quarters (columns 2-4);[4] controlling for additional lags of the MaPP and MP shocks, including the interaction terms with the nonbank dummy, to mitigate potential autocorrelation in the shocks (column 5); adding time fixed effects in Equation (1) of the main paper when computing the MaPP shocks (column 6); and re-estimating the same equation by adding directly the MP shocks as an independent variable to further

[4]While it is standard in quarterly-frequency analyses to lag monetary policy shocks by one quarter (Correa et al. 2022, Berger et al. 2024, Elliott et al. forthcoming), the appropriate horizon for MaPP shocks remains less clear. To ensure comparability in lending responses to shocks, we lag MaPP shocks by one quarter in the baseline. Our choice is supported by evidence from the macroprudential policy database for 28 EU countries, developed by Budnik and Kleibl (2018), which shows that the median of the difference between the announcement and in-force date of macroprudential measures is one quarter. To strengthen our findings, we run here a sensitivity analysis using alternative lag structures for the shocks.

mitigate the possible endogeneity in the response of MaPP shocks to macroeconomic conditions. Table E.5 shows that our results remain strongly robust to these sensitivity checks.

Table E.5: Alternative lag structures and shock specification

	(1) Lag 1	(2) Lag 2	(3) Lag 3	(4) Lag 4	(5) All Lags	(6) Time FE	(7) MP shocks
MP shock	-0.021***	-0.020***	-0.021***	-0.022***	-0.013***	-0.019***	-0.022***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)
MaPP shock	-0.019***	-0.018***	-0.019***	-0.019***	-0.015***	-0.020***	-0.016***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.001)
MP shock × Nonbank	0.046***	0.050***	0.054***	0.051***	0.016***	0.045***	0.049***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.003)	(0.003)
MaPP shock × Nonbank	0.016***	0.014***	0.014***	0.013***	0.016***	0.016***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)
Lender FE	✓	✓	✓	✓	✓	✓	✓
Firm × Time FE	✓	✓	✓	✓	✓	✓	✓
Observations	739,818	731,757	724,636	716,833	716,833	739,818	739,818
R^2	0.877	0.878	0.879	0.879	0.880	0.877	0.877

Notes: Dependent variable is the log of new syndicated loans. Column (1) uses the baseline MP and MaPP shocks lagged one quarter, as described in Section 2 of the main paper. In columns (2), (3), and (4) we lag the MP and MaPP shocks by respectively two, three, and four quarters. Column (5) includes lags one to four of the MaPP and MP shocks, along with their interactions with the nonbank dummy. Columns (6) and (7) make use of, respectively, MaPP shocks when controlling for time fixed effects and for MP shocks in Equation (1) of the main paper. Standard errors clustered by firm. Asterisks, *, **, and ***, denote statistical significance at the 10%, 5%, and 1% levels.

Regression-based approach for loan share imputation

We impute missing loan shares using the regression-based approach proposed by Blickle et al. (forthcoming), which accounts for post-origination changes in syndicate participation. Blickle et al. (forthcoming) document that U.S. lead arrangers often reduce their loan exposure after origination, a pattern that is especially pronounced for riskier Term B loans that are more frequently held by nonbanks. They provide a regression-based procedure to approximate post-origination loan shares for Dealscan users. We adapt their methodology to our Dealogic data to construct analogous estimates of post-origination participation shares. This imputation is subject to several limitations. First, the coefficients in Blickle et al. (forthcoming) are estimated using U.S. syndicated loans, whereas our sample spans multiple countries, which may introduce measurement error. Second, their analysis is conducted at the banking-group level, which obscures lender-level distinctions between banks and nonbanks that are central to our setting. Third, although lender-role variables are broadly comparable across Dealogic and Dealscan, the mapping is imperfect, although this is a minor point.

Despite these caveats, Table E.6 shows that our main conclusion, i.e., a differential increase in nonbank lending relative to bank lending following MaPP tightening, remains strongly robust. The estimated effects of MP shocks, however, lose statistical significance when controlling for borrower demand with firm×time fixed effects (column 4). Given the imprecision inherent in extrapolating post-origination share estimates beyond the original setting, these results should be interpreted with a pinch of salt.

Table E.6: Account for post-origination participation shares

	(1) Loans	(2) Loans	(3) Loans	(4) Loans	(5) Spread
MP shock	-0.039***	-0.002	-0.001	-0.000	-5.955
	(0.008)	(0.004)	(0.003)	(0.003)	(4.387)
MaPP shock	-0.022***	-0.008***	-0.007***	-0.007***	0.917
	(0.004)	(0.003)	(0.002)	(0.002)	(6.433)
MP shock × Nonbank		0.015***	0.011**	0.001	-17.468*
		(0.005)	(0.005)	(0.004)	(9.510)
MaPP shock × Nonbank		0.016***	0.017***	0.015***	-5.328
		(0.004)	(0.003)	(0.003)	(10.664)
Firm FE	✓	✓	✓		
Lender FE	✓	✓	✓	✓	
Country × Sector × Time FE		✓			
ILST FE			✓		
Firm × Time FE				✓	✓
Facility controls					✓
Observations	756,483	749,581	737,829	739,818	36,439
R^2	0.588	0.664	0.751	0.860	0.845

Notes: Dependent variable is the log of new syndicated loans with exception of column (5) referring to the spread expressed in bps. Column (5): data aggregated at the facility-borrower-quarter level, and *Nonbank* refers to the five-year share of nonbank loans over total loans for each borrower. Missing loans shares are estimated based on the regression results of Blickle et al. (forthcoming). Standard errors clustered by firm in columns (1)-(4), and by borrower country in column (5). Asterisks, *, **, and ***, denote statistical significance at the 10%, 5%, and 1% levels.

Alternative fixed effects, loans types, and extensive margin

We test the sensitivity of our results by: (i) controlling for region-specific time fixed effects to check whether different parts/regions of the world may load differently on the global financial cycle and thus potentially bias banks' and nonbanks; lending response to shocks;[5] (ii) controlling for cross-country differences, such as differences in regulatory frameworks in the lender-country; (iii) term loans versus credit lines;[6] (iv) looking at the extensive margin of lending;[7] and (v) excluding the top three nonbanks.[8]

Table E.7 shows that our baseline results remain robust to controlling for region-time fixed effects (column 2) or lender-country differences over time (column 3), to different loan types. i.e., term loans and credit lines (columns 4 and 5), to the extensive margin of lending (column 6), and to excluding the top three nonbanks from the sample in column (7), although the coefficient on the interaction term between MaPP shock and nonbanks is not estimated precisely.

Table E.7: Alternative fixed effects, loan types, and extensive margin

	(1) Baseline	(2) Region-time	(3) Lender-country	(4) Term loans	(5) Credit lines	(6) Ext. margin	(7) Exc. top 3 nonbanks
MP shock	-0.021***	-0.017***	-	-0.019***	-0.022***	-0.006***	-0.016***
	(0.002)	(0.004)		(0.003)	(0.003)	(0.001)	(0.002)
MaPP shock	-0.019***	-0.022***	-	-0.019***	-0.020***	-0.007***	-0.018***
	(0.002)	(0.003)		(0.002)	(0.002)	(0.001)	(0.002)
MP shock × Nonbank	0.046***	0.061***	0.036***	0.033***	0.056***	0.015***	0.029***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)	(0.003)
MaPP shock × Nonbank	0.016***	0.007**	0.020***	0.012***	0.021***	0.008***	0.001
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.001)	(0.002)
Lender FE	✓	✓	✓	✓	✓	✓	✓
Region × Time FE		✓					
Lender-country × Time FE			✓				
Firm × Time FE	✓		✓	✓	✓	✓	✓
Observations	739,818	751,501	739,806	348,399	522,973	2,119,524	689,587
R^2	0.877	0.697	0.878	0.899	0.896	0.931	0.879

Notes: Dependent variable is the log of new syndicated loans. Column 1 shows the benchmark specification, column 2 adds region × time fixed effects and column 3 lender-country × quarter fixed effects, columns 4 and 5 restrict the sample to term loans and credit lines, column 6 analyzes the extensive margin, and column 7 excludes the top three nonbanks. Asterisks, *, **, and ***, denote statistical significance at the 10%, 5%, and 1% levels.

[5] We follow the IMF region definition and assign borrower countries to one of six groups: Advanced Economies, Emerging and Developing Asia, Emerging and Developing Europe, Latin America and the Caribbean, Middle East and Central Asia, and Sub-Saharan Africa.

[6] Nonbanks are typically more active in term loans in the *secondary market*, but in the primary market (our data) they tend to be involved in both loan facilities.

[7] We follow Aldasoro et al. (2025) and expand our dataset with loan amounts of zero immediately before and after every quarter for which we observe loans for lender-borrower pairs.

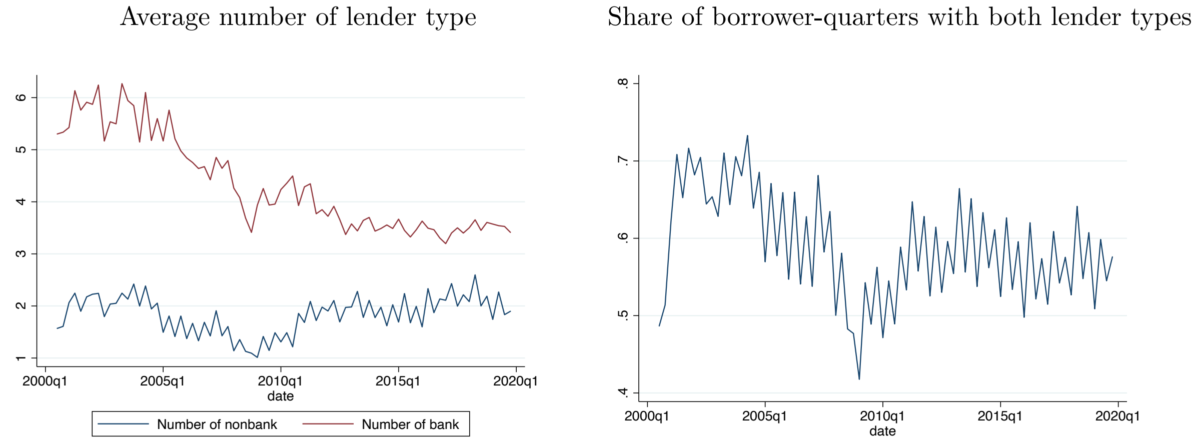
[8] JP Morgan Securities LLC, BofA Securities, and Citigroup Global Markets Inc. account, on average, for around 10 percent of syndicated lending by nonbanks over our estimation period 2000-19.

Restrictiveness of firm$\times$quarter fixed effects

Our preferred regressions control for demand with firm$\times$quarter fixed effects, thereby relying on the identification assumption of a nonfinancial firm borrowing from at least one bank and one nonbank in the same quarter. Although we have documented in the main paper that our results remain robust to relaxing this assumption—by controlling for demand with country$\times$industry$\times$quarter or ILST fixed effects—we further assess the restrictiveness of this assumption in two ways. First, we examine the evolution of borrower-lender composition by computing the average number of bank and nonbank lenders per borrower over time and the corresponding share of borrower-quarters with both lender types. Second, we re-estimate our baseline specification on a restricted sample that includes only borrower-quarters in which a given borrower simultaneously borrows from at least one bank and one nonbank lender.

Our new results indicate that the identification assumption is not overly restrictive. More than half of borrower-quarters feature both bank and nonbank lenders throughout the sample period, with only a temporary decline during the Global Financial Crisis (Figure E.1). Moreover, column (2) of Table E.8 shows that restricting the sample to borrower-quarters with both lender types yields estimates that are quantitatively and statistically similar to the baseline results. This restricted sample still accounts for 88 percent of lender–borrower–quarter observations, underscoring that our baseline results are not driven by a small or selected subset of borrowers.

Figure E.1: Borrower-lender characteristics



Notes: Left panel: the average number of bank and nonbank lenders that a borrower has over time. Right panel: the share of borrower-quarters with both lender types.

Table E.8: Testing the restrictiveness of borrower-quarter identification assumption

	(1)	(2)
MP shock	-0.021***	-0.022***
	(0.002)	(0.002)
MaPP shock	-0.019***	-0.019***
	(0.002)	(0.002)
MP shock × Nonbank	0.046***	0.048***
	(0.003)	(0.003)
MaPP shock × Nonbank	0.016***	0.017***
	(0.002)	(0.002)
Lender FE	✓	✓
Firm × Time FE	✓	✓
Observations	739,818	583,640
R^2	0.877	0.847

Notes: Dependent variable is the log of new syndicated loans. Column (1) shows the baseline results from column (4) of Table 2 in the main text. Column (2) estimates the baseline specification conditional on borrower-quarters with both bank and nonbank lenders. Standard errors clustered by firm. Asterisks, *, **, and ***, denote statistical significance at the 10%, 5%, and 1% levels.

Persistence in lending

Our dependent variable is the logarithm of loans which is standard in the syndicated loan literature using primary market data, and more broadly in studies of credit supply at the loan- or lender–borrower level. Our outcome variable captures the intensive margin of new syndicated lending activity in a given lender–borrower–quarter; the log transformation allows us to interpret coefficients as semi-elasticities while reducing the influence of extreme loan sizes. Since our dependent variable is new loan origination—a flow variable—rather than a stock measure of credit, it does not mechanically inherit the persistence properties typically associated with (credit) stock variables, and thus concerns about unit roots should be less relevant in this setting.

But it is possible that the persistence in lending may still lead our MP and MaPP coefficients to capture slow-moving credit dynamics rather than a causal response. Including the lagged dependent variable would address the persistence issue, but it would be particularly restrictive since firms do not borrow frequently in the syndicated loan market (the median duration of each loan is five years), and several lender–borrower pairs would have long stretches of zero activity over time. As a result, including the lagged dependent variable, or equivalently, using growth rates as the dependent variable, would lead us to drop a large number of observations from the estimation sample.

Moreover, in the syndicated loan market, however, such persistence does not naturally arise at the lender–borrower level. Borrowing relationships are episodic: loans are predominantly five-year bullet instruments (Table A.2 in the main paper), firms access the market infrequently, with fewer than three loans on average over the sample (Table E.9), and many lender–borrower pairs exhibit long gaps between originations, with roughly two loans on average from the same lender over the sample (Table E.9). By contrast, persistence may be a more meaningful feature at the *lender level* as bank and nonbank intermediaries adjust their lending capacity gradually due to balance-sheet constraints, funding conditions, and risk management considerations. Lagging aggregate lending by lender, rather than by lender–borrower, may therefor better control for slow-moving credit supply dynamics. This approach also has the benefit of preserving most of the observations included in the baseline specification.

Table E.9: Number of loans per nonfinancial borrower

	Mean	STD	P25	P50	P75
Number of loans per borrower	2.64	3.95	1.00	1.00	3.00
Number of loans per borrower-lender pair	1.78	1.82	1.00	1.00	2.00

Notes: Summary statistics from the syndicated loan market, restricted to non-financial borrowers based on their SIC code classification.

In this regard, we compute the lagged sum of loans for each lender-quarter, and include it as an additional regressor in Equation (2) of the main paper. Column (2) of Table E.10 shows that our main coefficients on MP and MaPP in the baseline specification in column (1) remain largely unchanged, alleviating concerns that the baseline results are driven by spurious persistence in lending.

Table E.10: Controlling for lagged loan dynamics

	(1) Baseline	(2) Include lag loans
MP shock	-0.021***	-0.022***
	(0.002)	(0.002)
MaPP shock	-0.019***	-0.019***
	(0.002)	(0.002)
MP shock × Nonbank	0.046***	0.053***
	(0.003)	(0.003)
MaPP shock × Nonbank	0.016***	0.017***
	(0.002)	(0.002)
$\text{Log(Loan)}_{l,t-1}$		0.015***
		(0.001)
Lender FE	✓	✓
Firm × Time FE	✓	✓
Observations	739,818	691,141
R^2	0.877	0.875

Notes: Dependent variable is the log of new syndicated loans. Column (2) includes the lag of new loans at the lender-level as an additional explanatory variable. Standard errors clustered by firm. Asterisks, *, **, and ***, denote statistical significance at the 10%, 5%, and 1% levels.

Additional robustness checks

We run further robustness checks: (i) pre-GFC (until 2007Q4) versus post-GFC periods (starting in 2010Q1); (ii) USD-denominated loans vs non-USD loans; (iii) cross-border versus domestic lending, with cross-border lending defined as loans where the borrower and lender are located in different countries, and domestic borrowing as loans when the country of the borrower and lender coincide; (iv) borrowers located in AEs or EMDEs; (v) and country-specific regressions for selected country lenders.

We find that our results are not sensitive to splitting the sample into the pre- and post-GFC period (columns 2 and 3 in Table E.11). Columns (4) and (5) indicate that increases in nonbank credit following the shocks is greater in USD lending, consistent with the narrative of lenders taking advantage of lower interest rate differentials with the US dollar in a context of the appreciation of the local currency against the US dollar caused by tighter domestic policy (Bruno and Shin 2015). Finally, we show that our baseline results hold when breaking down flows into cross-border versus domestic (columns 6 and 7), and borrowers from AEs or EMDEs (columns 8 and 9).

Table E.11: Robustness checks: split-sample specifications

	(1) Base	(2) Pre-GFC	(3) Post-GFC	(4) USD	(5) Non-USD	(6) Cross-border	(7) Domestic	(8) AE	(9) EMDE
MP shock	-0.021***	-0.004	-0.006*	-0.024***	-0.014***	-0.017***	-	-0.022***	-0.015**
	(0.002)	(0.005)	(0.003)	(0.003)	(0.004)	(0.003)		(0.002)	(0.007)
MaPP shock	-0.019***	0.002	-0.009***	-0.018***	-0.015***	-0.012***	-	-0.020***	-0.007
	(0.002)	(0.005)	(0.002)	(0.002)	(0.003)	(0.002)		(0.002)	(0.006)
MP shock × Nonbank	0.046***	0.015*	0.007*	0.058***	0.030***	0.028***	0.073***	0.048***	0.032***
	(0.003)	(0.009)	(0.004)	(0.004)	(0.005)	(0.004)	(0.006)	(0.003)	(0.010)
MaPP shock × Nonbank	0.016***	0.016*	0.008***	0.023***	-0.002	0.013***	0.019***	0.016***	0.027***
	(0.002)	(0.010)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.002)	(0.009)
Lender FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE × Time	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	739,818	276,500	403,576	448,199	305,420	236,380	475,731	696,915	42,297
R^2	0.877	0.854	0.893	0.831	0.909	0.837	0.892	0.880	0.820

Notes: Dependent variable is the log of new syndicated loans. Column (1) refers to our baseline specification in Table 1 of the main paper; column (2) includes the pre-GFC sample (up to 2007Q4); column (3) the post-GFC sample (after 2010Q1); column (4) includes only USD loans; column (5) only non-USD loans; column (6) refers to cross-border lending; column (7) to domestic lending (a loan is classified as cross-border if the borrower's country is different from the lender's country); column (8) restricts the sample to borrowers in advanced economies (AEs); column (9) restricts the sample to borrowers in emerging markets and developing economies (EMDEs). Standard errors clustered by firm. Asterisks, *, **, and ***, denote statistical significance at the 10%, 5%, and 1% levels.

We also find that our results are robust to restricting the specification to lenders from selected AEs, the U.S., U.K., France, and euro area (Table E.12).

Table E.12: Robustness checks: major country lenders

	(1) Baseline	(2) US	(3) UK	(4) FR	(5) EA	(6) US+UK+EA
MP shock	-0.021***	-	-	-	-0.259	-0.028***
	(0.002)				(0.361)	(0.003)
MaPP shock	-0.019***	-	-	-	-0.002	-0.017***
	(0.002)				(0.003)	(0.002)
MP shock × Nonbank	0.046***	0.128***	0.078***	0.040***	0.038***	0.059***
	(0.003)	(0.009)	(0.020)	(0.007)	(0.004)	(0.004)
MaPP shock × Nonbank	0.016***	0.028***	0.013	0.015**	0.009**	0.028***
	(0.002)	(0.005)	(0.010)	(0.007)	(0.004)	(0.003)
Lender FE	✓	✓	✓	✓	✓	✓
Firm FE × Time	✓	✓	✓	✓	✓	✓
Observations	739,818	287,195	37,690	36,275	159,526	526,796
R^2	0.877	0.842	0.821	0.871	0.868	0.841

Notes: Dependent variable is the log of new syndicated loans. Column (1) refers to the baseline specification in Table 1 of the main paper, column (2) includes only US lenders, column (3) only UK lenders, column (4) only French lenders, column (5) only euro area lenders, and column (6) includes lenders from all these previous countries. Standard errors clustered by firm. Asterisks, *, **, and ***, denote statistical significance at the 10%, 5%, and 1% levels.

Alternative clustering methods

We examine the impact of different standard error clustering approaches. Table E.13 confirms that our main results remain robust under various clustering strategies: firm and country-time (column 2), lender country-time (column 3), and firm, and lender country-time (column 4).

Table E.13: Alternative clustering methods

	(1)	(2)	(3)	(4)
MP shock	-0.021***	-0.021***	-0.021***	-0.021***
	(0.002)	(0.003)	(0.003)	(0.003)
MaPP shock	-0.019***	-0.019***	-0.019***	-0.019***
	(0.002)	(0.003)	(0.002)	(0.002)
MP shock × Nonbank	0.046***	0.046***	0.046***	0.046***
	(0.003)	(0.005)	(0.005)	(0.005)
MaPP shock × Nonbank	0.016***	0.016***	0.016***	0.016***
	(0.002)	(0.004)	(0.004)	(0.004)
Lender FE	✓	✓	✓	✓
Firm × Time FE	✓	✓	✓	✓
Observations	739,818	739,818	739,818	739,818
R^2	0.877	0.877	0.877	0.877

Notes: Dependent variable is the log of new syndicated loans. Standard errors clustered by firm (column 1), firm and country-time (column 2), lender country-time (column 3), and by firm, and lender country-time (column 4). Asterisks, *, **, and ***, denote statistical significance at the 10%, 5%, and 1% levels.

Interaction between monetary and macroprudential policy shocks

Monetary policy can amplify or mitigate the effectiveness of macroprudential policies, and vice-versa (Altavilla et al. 2020, Gambacorta and Murcia 2020, Imbierowicz et al. 2021). Table E.15 tests for these possible amplification/mitigation effects. When not distinguishing banks from nonbanks, we find that MaPP and MP shocks complement each other in reducing credit supply to corporate borrowers (column 1). This echoes the results in Altavilla et al. (2020), who use credit registry data for several European countries over 2012-17 to find that the easing of both MP and MaPP amplify bank lending to both nonfinancial corporations and households in the euro area. Although our estimate is statistically significant at conventional levels, the economic magnitude is small: a one-standard deviation increase in both shocks leads to an additional decline in lending to nonfinancial corporations of 0.5 percent. This is consistent with Gambacorta and Murcia (2020), who find that the tightening of both policies reinforce the fall in credit growth in five Latin American countries, but that the effect is quantitatively small.

We add the interaction terms with nonbanks in column (2). The coefficient on the interaction term of both shocks flips to positive when isolating the effect for banks only: the tightening of both policies mitigates the credit supply contraction from banks by 0.3 percent. This is again of a relatively small magnitude compared to the individual effects of each policy tightening (2.1 percent for MP shocks and 1.8 percent for MaPP shocks). In turn, we find that the expansion of nonbank credit to be mitigated by 1.4 percent when both policies tighten (coefficient on triple interaction term), although nonbanks still increase their lending supply relative to banks, with a combined effect in the order of 4.2 percent (4.2 = 4.6 + 1.0 - 1.4).

To better understand the interaction between MP and MaPP shocks, we look into all possible tightening-loosening combinations for banks and nonbanks. We show that the different monetary-macroprudential policy combinations exhibit a roughly balanced number of observations in each bucket (Table E.14). Starting with bank lending, and focusing on the tightest specification in column (5), we only find a statistically significant effect when MP loosens and MaPP tightens ($MP^{-} \times MaPP^{+}$). Although the coefficient on MP tightening and MaPP loosening is not precisely estimated, we also find that it is negative. This suggests that that the lack of policy coordination, i.e., MP loosening and MaPP tightening, or vice-versa, typically leads to an additional contraction in bank lending. For instance, our estimates indicate that while an easing of monetary policy stimulates bank lending, a simultaneous tightening of macroprudential policy seems to fully offset that expansion (-0.3 = 2.2 - 1.8 - 0.7).

Moving to nonbanks (last four rows), we can rationalize the negative coefficient we have found in column (2) as being driven by a combined tightening of MP and MaPP: the expansion of nonbank lending relative to banks in this scenario is mitigated by 2.3 percent. However, we note that nonbanks still expand lending relative to banks by 4.2 percent, when summing all relevant coefficients (4.2 = 5.3 + 1.2 - 2.3). By contrast, the expansion of nonbank credit relative to banks seems to be amplified when there is a divergence in the direction between MP and MaPP (as discussed previously).

Table E.14: Distribution of sample across shocks combination

Shock	Observations
$MP^{+} \times MaPP^{+}$	211,193
$MP^{+} \times MaPP^{-}$	152,024
$MP^{-} \times MaPP^{+}$	199,871
$MP^{-} \times MaPP^{-}$	176,730
Total	739,818

Notes: Total number of observations for each monetary policy-macroprudential policy shocks combination.

Table E.15: Interaction between monetary and macroprudential policy shocks

	(1)	(2)	(3)	(4)	(5)
MP shock	-0.007***	-0.021***	-0.027***	-0.028***	-0.022***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)
MaPP shock	-0.012***	-0.018***	-0.017***	-0.017***	-0.018***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
MP shock × Nonbank		0.046***	0.067***	0.068***	0.053***
		(0.003)	(0.006)	(0.005)	(0.005)
MaPP shock × Nonbank		0.010***	0.012***	0.014***	0.012***
		(0.003)	(0.004)	(0.003)	(0.003)
MP shock × MaPP shock	-0.005***	0.003*			
	(0.001)	(0.002)			
MP shock × MaPP shock × Nonbank		-0.014***			
		(0.003)			
$MP^+ \times MaPP^+$			0.016***	0.011***	0.002
			(0.005)	(0.004)	(0.003)
$MP^+ \times MaPP^-$			-0.006	-0.004	-0.005
			(0.005)	(0.005)	(0.004)
$MP^- \times MaPP^+$			-0.013***	-0.012***	-0.007**
			(0.005)	(0.004)	(0.003)
$MP^- \times MaPP^-$			-0.001	-0.005	-0.003
			(0.005)	(0.004)	(0.004)
$MP^+ \times MaPP^+ \times$ Nonbank			-0.033***	-0.029***	-0.023***
			(0.008)	(0.007)	(0.006)
$MP^+ \times MaPP^- \times$ Nonbank			0.003	0.005	0.009*
			(0.007)	(0.006)	(0.005)
$MP^- \times MaPP^+ \times$ Nonbank			0.019**	0.020***	0.023***
			(0.007)	(0.006)	(0.006)
$MP^- \times MaPP^- \times$ Nonbank			0.002	0.007	-0.002
			(0.007)	(0.006)	(0.005)
Firm FE			✓	✓	
Lender FE	✓	✓	✓	✓	✓
Country × Sector × Time FE			✓		
ILST FE				✓	
Firm × Time FE	✓	✓			✓
Observations	744,981	739,818	749,581	748,405	739,818
R^2	0.877	0.877	0.727	0.795	0.877

Notes: Dependent variable is the log of new syndicated loans. Standard errors clustered by firm. Asterisks, *, **, and ***, denote statistical significance at the 10%, 5%, and 1% levels.

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