Global Banks' Macroeconomic Expectations and Credit Supply *

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Abstract

We examine how global banks' macroeconomic expectations shape credit supply. Comparing banks lending to the same firm within the same tranche, we find that greater GDP growth optimism is associated with greater credit supply. A one-standard-deviation increase in a bank's growth forecast for the borrower's country is associated with a 1.4-percentage-point higher loan share and 15% more lending to that country, or $133 million per month. The association is driven by participant lenders, strengthens with forecaster disagreement, intensifies at the onset of credit booms, and disappears after macroprudential tightening. Inflation expectations, by contrast, have no significant association with credit supply.

Keywords: Expectations; Asymmetric Information; Global Banks; Credit Supply

JEL Codes: E32; F34

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1 Introduction

Expectations govern the fundamental economic decisions underlying macroeconomic dynamics (Coibion and Gorodnichenko, 2015; Gennaioli, Ma, and Shleifer, 2016). Within international financial markets, aggregate evidence similarly identifies information as a primary driver of cross-border capital flows (Portes, Rey, and Oh, 2001; Tille and Wincoop, 2014). While financial intermediaries—particularly global banks—are central to mediating these activities (Gabaix and Maggiori, 2015; Gabaix and Koijen, 2021), the precise influence of their macroeconomic expectations remains largely unexplored.

Do global banks' forecasts regarding destination-country GDP growth and inflation significantly affect international bank lending? Relatedly, what characterizes their expectation formation process, and does this underlying mechanism subsequently mediate the transmission of macroeconomic beliefs to actual credit supply? Resolving these fundamental questions is critical for advancing our understanding of global banking flow dynamics. Ultimately, answering them yields vital insights for macroprudential policymakers aiming to manage and regulate cross-border financial stability.

Answering these questions poses two empirical challenges. The first is data availability: linking banks' macroeconomic forecasts to their contemporaneous lending requires granular data rarely observed jointly. The second is identification: expectations and lending may respond to common economic conditions, while lending itself may shape expectations through its effects on economic activity.

We overcome these empirical hurdles in two ways. First, we utilize a novel dataset yielding monthly observations of global banks' macroeconomic expectations across destination economies. We then merge these explicit forecasts with granular syndicated loan records and bank balance-sheet data. Second, to address endogeneity, we exploit the granular structure of our data—where multiple banks with heterogeneous expectations lend concurrently to the exact same firm—allowing us to analyze within-loan-tranche variation across banks. Saturating the estimation with loan-tranche fixed effects absorbs

unobserved borrower demand and the realized fundamentals of the borrower's country, while bank-borrower-country fixed effects absorb any persistent affinity of a bank for a country, so that identification rests on changes in a bank's own outlook for a country relative to its co-lenders. We buttress this design in three ways. Bounding exercises for selection on unobservables (Oster, 2019) indicate that unobservables would have to be several times as influential as the full set of controls and fixed effects, and selected in the opposite direction, to eliminate the effect. Randomization tests that replace the bank's forecast with another bank's forecast for the same country, or with the bank's own forecast for another country, yield placebo coefficients centered at zero. And the effect is confined to the forecast made in the month before signing, is unrelated to the bank's share in its previous loan to the country, and is absent from the decision to join a syndicate, which together rule out slow-moving lending strategies and bank-wide sentiment as alternative explanations.

Our empirical results proceed in four parts: characterizing the expectation formation process, establishing its direct effect on bank lending, uncovering the mechanism through which beliefs are transmitted to credit, and examining how this transmission depends on the state of the credit cycle and policy.

First, following Coibion and Gorodnichenko (2015), we reject the full-information rational expectations (FIRE) null, documenting significant information rigidities in global banks' GDP forecasts. Specifically, the estimated probability of information updating—or the weight assigned to new signals—is approximately 0.74, a magnitude on par with corporate and non-bank financial forecasters. Furthermore, implementing the diagnostic tests of Bordalo, Gennaioli, Ma, et al. (2020) and Gemmi and Valchev (2026), we reveal that global banks place relatively more weight on idiosyncratic signals than on public ones.

Second, we establish that macroeconomic expectations exert a first-order impact on global banks' lending decisions. Specifically, an optimistic outlook regarding a destination country's GDP growth drives an expansion in credit supply to local borrowers. Quantita-

tively, a one-standard-deviation increase in a bank's GDP growth forecast for a borrower country increases its loan share by 1.4 percentage points, 8% of the mean share, and the belief differences among co-lenders of a typical syndicate reallocate about 0.2 percentage points of every deal from its less to its more optimistic members. These within-syndicate tilts accumulate: at the bank-country level, the same increase in expectations raises a bank's share of all credit to the country by 0.9 percentage points, its lending volume by 15%, or about $133 million per month, and the average spread on its new loans by 15 basis points. Better opportunities in a bank's other markets work in the opposite direction: a one-standard-deviation improvement in its abnormal expected growth elsewhere lowers its share of a loan by roughly half as much as an equal improvement in its view of the borrower's country raises it, so beliefs reallocate a bank's syndicate exposure across countries rather than only scaling it. The baseline result survives a comprehensive battery of sensitivity checks, including alternative constructions of loan shares, controls for interest rate expectations, the exclusion of refinancings and of the US domestic market, and heterogeneous bank and time-period subsamples, and it is unchanged by the length of the bank-firm relationship and by whether the loan is cross-border or in foreign currency.

Third, we trace the mechanism. The transmission of beliefs to credit operates through participant lenders rather than lead arrangers, whose shares are set by their underwriting role, and on the intensive margin of how much a bank lends within a syndicate rather than on whether it joins one. It is stronger when forecasters disagree about the borrower country and for borrowers in less cyclical sectors, where a bank's own macroeconomic view is least substitutable by common information. Utilizing bank-level estimates of expectation formation, we find that over- or underreaction per se does not alter the pass-through, but that lending responds less to the forecasts of banks that underweight public information, consistent with such forecasts being noisier measures of the beliefs that guide lending. Finally, the transmission depends on the bank's capacity to act: a bank's lending responds more to its expectations when its balance sheet is stronger than its own norm. Together, these results indicate that beliefs matter where they fill an informational gap

left by what the syndicate already knows, and where the bank has the room to act on them.

Fourth, the transmission is state dependent. Lending becomes markedly more sensitive to current expectations at the onset of credit booms in the borrower country, and the response is driven by current forecasts rather than by a bank's habitual optimism. It switches off in the year after a macroprudential tightening in the borrower country. In stark contrast to GDP growth forecasts, global banks' inflation expectations for a destination country exert no statistically significant impact on credit supply, either on their own, jointly with growth expectations, or in high-inflation episodes. This muted effect has a natural institutional explanation: syndicated loans are priced over floating benchmark rates, so expected inflation is hedged by contract design, whereas expected growth maps directly into borrower repayment capacity.

In sum, we are the first to show with granular data that global banks' macroeconomic expectations—which exhibit information rigidities and a relative overweighting of idiosyncratic signals—significantly drive credit supply and lending volumes, with the transmission strongest precisely where a bank's own view fills a gap left by common information and weakest where regulation constrains lending.

The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 introduces the data on expectations and syndicated lending. Section 4 characterizes the expectation formation process. Section 5 outlines the identification strategy, presents the baseline results and robustness checks, examines the mechanism through which beliefs are transmitted to credit, and shows how syndicate-level allocations respond to a bank's opportunities in other countries and aggregate to bank-country lending. Section 6 studies how the transmission depends on the credit cycle and on macroprudential policy, and turns to inflation expectations. Finally, Section 7 concludes. Figure 1 summarizes the structure of the analysis and the main results.

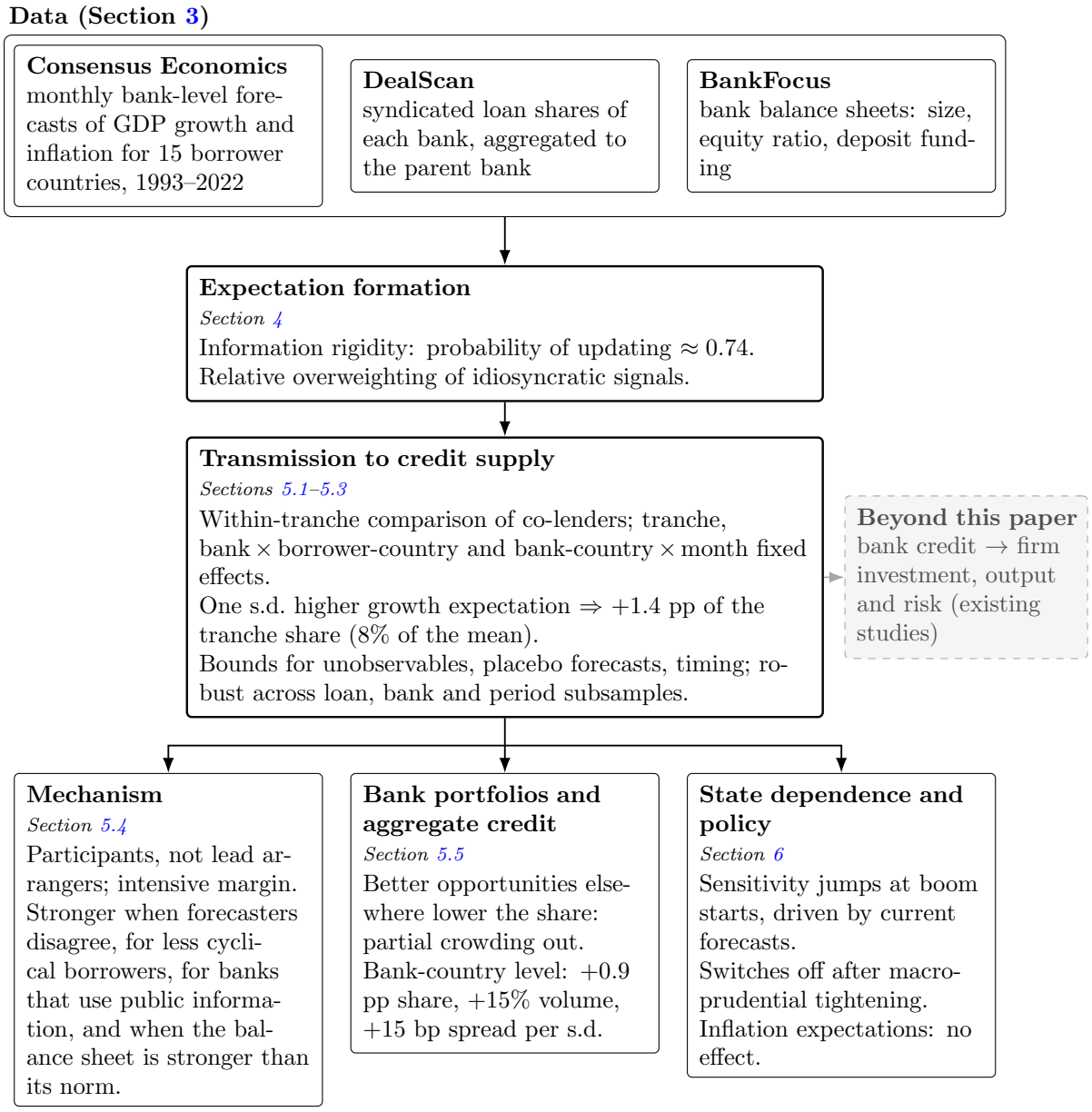


Figure 1: Roadmap of the Paper

Notes: The figure summarizes the structure of the analysis and the main results. Numbers refer to the baseline estimates reported in the sections indicated; s.d. denotes one standard deviation of a bank's GDP growth expectation for a borrower country.

2 Related Literature

Our paper contributes to four different strands of literature. First, we build on the literature exploring information rigidities and macroeconomic belief formation. Coibion and Gorodnichenko (2015) pioneer a framework to empirically test the full-information rational expectations (FIRE) hypothesis, quantifying how information rigidities co-move with macroeconomic volatility. Extending this paradigm, Bordalo, Gennaioli, Ma, et al. (2020) and Afrouzi, Kwon, Landier, et al. (2023) rationalize overreaction in macroeconomic forecasts by embedding diagnostic expectations and costly information processing within dispersed-learning models. Furthermore, Gemmi and Valchev (2026) document that professional forecasters face strategic incentives to optimally "stand out" by overweighting idiosyncratic signals, while Benhima, Blengini, and Merrouche (2026) establish that local agents possess persistent informational advantages over foreign forecasters regarding domestic macroeconomic fundamentals. Focusing specifically on inflation expectations, Malmendier and Nagel (2016) demonstrate that lifetime inflation experiences shape belief dispersion, Malmendier and Nagel (2026) show through an experience-based learning model that even long-run inflation expectations are never fully anchored, and Dräger, Lamla, and Pfajfar (2024) show that recent inflation news directly shifts forward-looking expectations.

We advance this broad literature by characterizing the expectation formation of global banks, a set of agents whose beliefs translate directly into credit, and by showing which features of that process matter for transmission: the pass-through of beliefs to lending is weakest for banks that underweight public information, whereas over- or underreaction per se leaves it unchanged. Ultimately, by connecting these expectational frictions directly to lending, we underscore the critical value of utilizing actual survey expectations to decode real economic behavior.

The second strand of literature explores how expectations drive business cycles, a tradition tracing back to Minsky (1977). He posited that boom-bust cycles in credit and out-

put are fundamentally governed by the shifting expectations of economic agents. Specifically, excessive optimism among managers and investors fuels over-borrowing and over-investment, systematically precipitating economic downturns. Building on this framework, recent empirical scholarship documents how firms' subjective expectations dictate their investment, production, and debt issuance, particularly under financial frictions (Gennaioli, Ma, and Shleifer, 2016; Ropele, Gorodnichenko, and Coibion, 2022; Gulen, Ion, Jens, et al., 2024; He, Su, and Yu, 2024). Furthermore, Cascaldi-Garcia (2024) analyze the macroeconomic propagation of news shocks, while De La O and Myers (2024) and Bigio, Silva, and Zilberman (2026) demonstrate that belief dispersion significantly distorts equilibrium asset prices, risk premia, and real activity.

We advance this literature by strictly holding constant borrower-side fundamentals, credit demand, and firm expectations, thereby cleanly isolating how banks' macroeconomic beliefs dictate aggregate credit supply. We also provide direct evidence on the cyclical dimension that this literature emphasizes: lending becomes markedly more sensitive to banks' current growth expectations at the onset of credit booms, and this sensitivity rises with disagreement among forecasters. At the same time, beliefs reach credit only to the extent that banks can act on them. Within a bank, the transmission strengthens when its balance sheet is stronger than its own norm, and the finding that macroprudential tightening in the borrower country severs the link between bank optimism and credit supply connects, in turn, to the evidence that such tools dampen bank credit growth (Cerutti, Claessens, and Laeven, 2017; Alam, Alter, Eiseman, et al., 2025): our results indicate that both the bank's own slack and the regulatory stance determine how far belief-driven lending goes.

Third, direct investigations into banks' macroeconomic expectations have historically been scarce, though this literature is expanding rapidly given the central role of financial intermediaries. Bassett, Chosak, Driscoll, et al. (2014) construct a credit supply shock using changes in lending standards from the Federal Reserve's Senior Loan Officer Opinion Survey (SLOOS), documenting its substantial effect on lending capacity. Ma

(2015) develop a proxy for bank CEO optimism based on insider stock holdings, linking managerial sentiment to pre-crisis real estate loan expansions and subsequent losses. Ma, Paligorova, and Peydro (2021) employ localized expectations of US banks regarding house prices and unemployment to establish a link between bank beliefs, credit supply, and real economic outcomes. Furthermore, Claessens, Ongena, and Wang (2023) utilize US bank data to identify how private information shapes loan terms and performance. Falato and Xiao (2023) attribute the subdued bank lending observed after the global financial crisis to over-pessimistic bank beliefs. More recently, D'Acunto, Gao, Liu, et al. (2025) elicit the subjective macroeconomic expectations of loan officers at a major Chinese platform via a survey experiment, confirming that these beliefs directly govern credit supply.

We distinguish our work from these single-country studies by examining global banks' macroeconomic expectations for GDP growth and inflation across borrower countries. While our findings corroborate the expectation-lending nexus documented in prior work, our primary focus diverges from concurrent studies. For instance, De Marco and Friedheim (2025) emphasize how banks' inflation expectations drive credit allocation, finding prominent Fisher effects. Although our inflation results align with theirs for the average firm, we instead uniquely isolate economic growth expectations and demonstrate their distinct implications for aggregate credit supply.

Our results also speak to the literature on the structure of loan syndicates. Sufi (2007) and Ivashina (2009) show that lead arrangers retain larger shares when information asymmetries about the borrower are severe, so that lead shares are pinned down by the lead arranger's monitoring and certification role. We complement this view by documenting the allocation among the remaining members: participants scale their shares with their own macroeconomic outlook, whereas lead arrangers' shares do not respond to their beliefs, and beliefs affect how much a bank lends within a syndicate rather than whether it joins one.

Finally, we contribute to the expanding literature linking macroeconomic expectations to international capital flows. Malmendier and Nagel (2016) explore experience-

based learning to explain international portfolio investments, while Cimadomo, Claeys, and Poplawski-Ribeiro (2016) and D'Agostino and Ehrmann (2014) tie fiscal balance expectations to sovereign bond spreads. Stavrakeva and Tang (2024) incorporate macroeconomic news and survey expectations to reconnect fundamentals with exchange rate dynamics. More closely related to our framework, Benhima and Cordonier (2022) emphasize how sentiment shocks and imperfect information drive the comovement of gross capital inflows and outflows. De Marco, Macchiavelli, and Valchev (2022) evaluate how information heterogeneity shapes the allocation of banks' sovereign portfolios, and Benhima, Blengini, and Merrouche (2026) attribute foreign currency borrowing in bond markets to expectation disagreements between international and domestic agents. Furthermore, Benhima, Bolliger, and Davenport (2023) rely on economic growth expectations to trace co-ownership spillovers, showing that pessimistic beliefs regarding one country can severely restrict mutual fund flows to others within the same portfolio.

We align with this broader literature by showing that macroeconomic expectations about a destination country govern credit to that country's borrowers, whether the bank sits inside or outside its borders. However, we explicitly depart from these studies of portfolio and bond market flows by focusing squarely on global banks and their active role in direct credit provision,[1] and by exploiting disagreement among banks as the source of identifying variation, in the spirit of Benhima, Blengini, and Merrouche (2026).

3 Data and Variable

3.1 Macroeconomic Expectation

To measure banks' macroeconomic expectations, we use data from Consensus Economics (CE). In the literature on expectations, various databases have been utilized to gauge

[1] In a different setting Kempf, Luo, Schäfer, et al. (2023) recently study how changes in countries' governmental political directions following elections and alignments with those of the lending banks result in changes to banks' macroeconomic expectations and credit granting. Expanding their focus, we more generally study bank macroeconomic expectation formation and its impact on credit granting along many different characterizations and dimensions.

professional forecasters' or CFOs' outlooks on the economy, corporate investment, and employment, as well as analysts' forecasts for earnings per share. Examples include the Survey of Professional Forecasters (SPF) conducted by the Federal Reserve Bank of Philadelphia, the Duke-CFO Magazine Business Outlook Survey, and the Institutional Brokers Estimate System (IBES), all of which focus on firms' expectations. Until recently, limited data has been available to measure banks' expectations. Notable exceptions include the Federal Reserve's Senior Loan Officer Opinion Survey (SLOOS), Blue Chip surveys, and the Federal Reserve's FR Y-14A data. However, these datasets cover only a small number of banks and are restricted to U.S. financial institutions' expectations about the domestic economy. Notably, to the best of our knowledge, CE is the only database that provides international banks' macroeconomic expectations regarding foreign economies.

CE conducts surveys among professional forecasters from various organizations and reports average values across respondents as the consensus forecast. We access the micro-level data, which identifies the name of each forecasting institution and their individual forecasts. We can classify forecasting institutions into six categories: commercial banks, non-bank financial institutions, consulting and rating agencies, non-financial firms, industry associations, and universities and research institutes. This paper focuses on commercial banks. After data cleaning (details provided below), the dataset includes 428 forecasting institutions, of which 195 are banks. Among these, 121 banks provide GDP growth forecasts for at least two countries. The forecasts span a long period, ranging from as early as the 1990s to the most recent months. On average, each bank-country pair has 202.7 forecasts. Table A1 presents the distribution of forecasting institutions by type.

Specifically, CE surveys are conducted in the first week of each month, with results published in the second week. Each survey collects forecasts for several macroeconomic variables, with availability varying across institutions. Our main analysis focuses on GDP growth rate forecasts, while inflation rate forecasts are incorporated in subsequent

discussions. These two variables are not only the most significant indicators of macroeconomic conditions but also the most extensively covered in the CE database.[2] In each month, the forecaster provides the expectation of the GDP growth rate and inflation rate in the current and next year. This means that, for a given year k, each institution makes 24 forecasts, starting in January of year $k-1$ and ending in December of year k. We clean the raw data following the procedure outlined in Bordalo, Gennaioli, Ma, et al. (2020). Specifically, we winsorize outliers by removing, for each country-forecast horizon (current or next year) in a given month, forecasts that deviate by more than five interquartile ranges from the median. Additionally, we retain only forecasters with at least ten observations.

As an illustration, Figure A1 in the appendix plots the current-year GDP growth forecasts of all banks in the CE database for the G5 economies (the United States, Germany, Japan, the United Kingdom, and France), for every month between 1990 and 2023, together with the mean forecast across banks in each month. We observe that forecasts move together with the business cycle and are revised sharply at turning points, most visibly in the 2008–2009 financial crisis and in 2020, when banks cut their forecasts by several percentage points within a few months and then revised them back up as the recovery took shape. More importantly for our analysis, banks disagree: in every month the forecasts are dispersed around the mean, and the dispersion widens precisely at the turning points, when uncertainty about the outlook is particularly high. This disagreement among banks regarding macroeconomic growth expectations provides the variation we exploit when examining the role of these expectations in their lending decisions.

Figure 2 illustrates the standard deviations of GDP growth rate expectations for the same country-year across a 24-month forecasting horizon. As described earlier, each bank provides 24 forecasts for a given country and year, and the variations depicted in the figure arise from differences across banks. The figure reveals significant disagreement in initial

[2]Other macroeconomic variables included in the CE database but less frequently forecasted include the 3-month interbank rate, 10-year government bond yield, unemployment rate, and current account balance, among others.

forecasts, which diminishes as the forecasting horizon shortens. This pattern is intuitive, as more information about economic fundamentals becomes available and is realized over time.

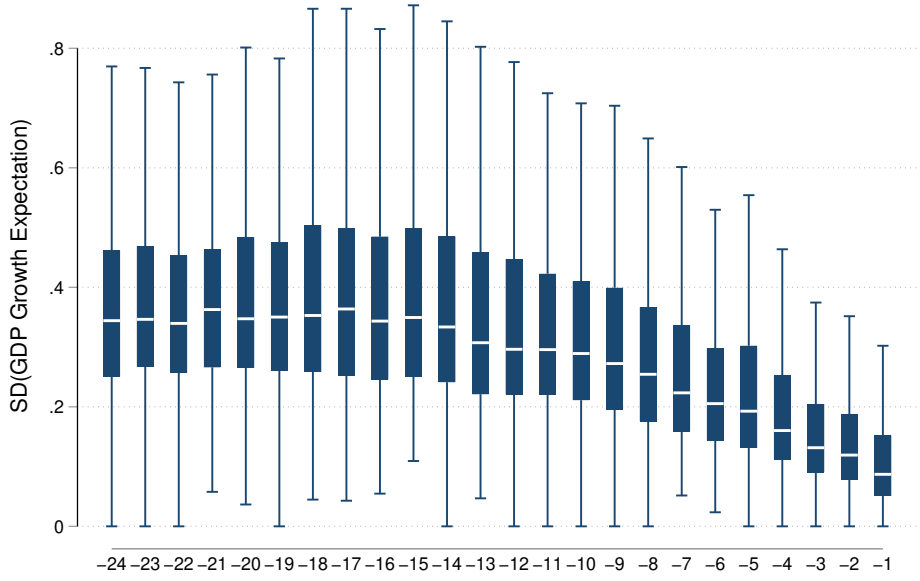


Figure 2: SD of GDP Growth Expectation Over the 24 Months Horizon

Notes: This figure shows the distribution of the standard deviations (SD) of GDP growth forecasts by forecasting horizon. The variation in SD reflects differences across forecasted country-year pairs.

3.2 Loan Data and Bank Characteristics

For lending information, we use loan-level data from DealScan, which is sourced from Thomson Reuters LPC and covers the universe of syndicated loans. These are large loans that are structured, arranged, and administered by a group of financial institutions as the lending amount and risk therein is beyond the capacity of a single lender. A typical syndicated loan is organized by one or more banks acting as the lead arrangers or lead underwriters, who arrange the composition of the lenders and specific loan terms. Specifically, the DealScan data is structured as multiple tranches ("facilities") within each deal ("package"), and each tranche is treated as an individual loan. We follow the literature and clean the DealScan data as described in Section A1 in the appendix. After the data cleaning procedure, we have 171,221 deals and 259,078 tranches originated

between October 1989 and December 2023, involving 10,638 parent banks and 71,649 borrowers.

For each loan, we know a rich set of information on the origination such as the date and the identity of the borrower and the bank, and the details of loan terms including the total amount, interest rate, and maturity. The variations across banks within a loan tranche are shown in their loan shares, which measures the credit supply by each bank and is the key explained variable in our study. A big issue with the DealScan database is the large fraction (about 70%) of missing values of the loan share variable.[3] The literature suggests imputing the lender share by allocating the loans equally for the missing shares (De Haas and Van Horen, 2013), but this will result in large measurement errors. Therefore, we stick with the small sample of un-imputed shares in the main analysis, and report that our main findings still hold with the larger but imputed sample.[4] We also access the banks' balance sheet data from BankFocus (formerly known as BankScope) and obtain bank characteristics, including size (measured as total assets), leverage (proxied by the equity-to-asset ratio), and funding structure (measured by the depository funding-to-asset ratio). The final sample used in the regression is the result of the availability of data in the three databases (i.e., CE, DealScan, and BankFocus) and we merge them at the bank-level. Since only banks that report forecasts to CE enter the sample, we examine how these banks and their loans compare with the rest of each database.[5] Note that the

[3]Table A8 in the appendix compares bank-tranche observations with and without a reported share.

[4]Because loan share is our dependent variable, imputing missing shares equally across banks removes bank-specific variation and attenuates the estimates. Appendix Table A7 supports this interpretation. Restricting the sample to fully reported tranches yields slightly larger estimates than the baseline. Adding imputed shares expands the sample and roughly halves the coefficient, which remains significant. Excluding fully imputed tranches restores the coefficient to near its baseline value, while estimates based solely on imputed observations are insignificant. Appendix Table A9 compares the baseline sample with the observations added through imputation.

[5]Appendix Table A5 compares 195 CE GDP forecasters across three groups: banks unmatched to DealScan, matched banks excluded for missing balance sheet data or loan shares, and regression-sample banks. Sample banks are larger, cover more countries and longer periods, and allocate a smaller share of forecasts to G5 economies. Yet their mean deviations from consensus, shares of above-consensus forecasts, and revision frequencies are statistically indistinguishable across groups. Table A6 compares roughly 1.4 million cleaned DealScan bank-tranche observations by CE-match status. Matched banks' loans are larger, occur earlier in the sample, and more often involve cross-border lending and G5 borrowers; syndicate size, lead-arranger share, maturity, and spreads are similar. Finally, Table A10 shows that banks with forecast data hold larger loan shares in the full DealScan sample, but bank and bank-country fixed effects explain this difference, and their shares respond similarly to consensus forecasts.

CE database provides only the names of banks, without any unique identifiers that could be matched with other databases. Therefore, we manually create a concordance between the banks in CE and those in DealScan for syndicated loans, as well as BankFocus for financial information.[6] Of the 195 banks in CE, 112 are matched to parent banks in DealScan, and 160 are matched to banks in the BankFocus databases. Because forecasts are reported by the parent bank, we define the lending unit at the same level: within each tranche, the shares of all affiliates belonging to the same parent are summed into a single parent-level observation, so that a bank-tranche observation records the parent's total commitment.[7]

As a result, the final dataset for the baseline analysis with un-imputed loan shares comprises 6,897 deals and 9,452 tranches originated between March 1993 and December 2022.[8] These transactions involve 62 global banks headquartered in 15 countries and 4,221 borrowers headquartered in 15 countries.[9] Table 1 presents summary statistics of the key variables used in this study, with their definitions provided in Table A2 in the appendix.[10]

Figure A2 in the appendix illustrates the lending activities and data structure used in this study. As an example, in June 2015, a loan tranche totaling $3.77 billion was issued to PepsiCo, a U.S. food company known for its flagship products Pepsi and Lay's.

[6]This process is assisted with the fuzzy match command in Stata, however, every bank/forecasting institute name is manually check since abbreviations are largely used in the Consensus Economics. For cases of mergers and acquisitions of banks, we try our best to ensure that we are using the correct periods of the correct financial institutions based on the time the forecast was made.

[7]This affects 8% of the observations in the full sample. A parent's share is set to missing only if none of its affiliates reports a share, and is capped at 100%. The parent is classified as a lead lender if any of its affiliates acts in a lead role, and the number of lenders in a tranche counts distinct parents.

[8]Ending the sample in 2019 to exclude the COVID period leaves the estimate essentially unchanged. The results are presented in Table A11 in the appendix.

[9]The 15 bank countries are: Argentina, Belgium, Canada, Denmark, France, Germany, Italy, Japan, Netherlands, Norway, Spain, Sweden, Switzerland, United Kingdom, and United States. The 15 borrower countries are Belgium, Canada, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, Norway, Spain, Sweden, Switzerland, United Kingdom, and United States. Table A3 in the appendix lists the 62 global banks.

[10]Table A4 in the appendix presents the characteristics of the tranches in the cleaned DealScan dataset, excluding consideration of the availability of bank expectation data. We observe that the loan shares and the number of banks are comparable between our sample and the full sample; however, the average tranche amount tends to be larger, while the maturity tends to be shorter in our sample after imposing the restriction on the availability of expectation data.

Table 1: Summary Statistics

	Mean	Standard Deviation	Min	Max	N
Loan Share	16.527	13.732	0.500	100.000	25752
L.GDP Growth Expectation	1.963	1.730	-6.700	7.400	25752
L.Ln(Asset)	13.941	2.584	7.428	21.543	25752
L.Equity/Asset Ratio	6.133	3.035	1.997	86.636	25752
L.Deposit/Asset Ratio	65.569	12.178	1.957	93.779	25752
L.Ln(Outstanding Loans)	10.971	1.576	3.557	13.375	25752
Number of Banks	12.275	9.036	2.000	156.000	25752
Ln(Tranche Amount)	5.381	1.787	-0.968	10.800	25752
Tranche Maturity	52.814	34.289	1.000	462.000	25752

Notes: This table presents the summary statistics of the key variables used in this study. The definitions of these variables are provided in Table A2 in the appendix.

This loan was financed by 22 banks. Within this tranche, we observe the GDP growth expectations and loan shares of HSBC and UBS, two global banks headquartered in the UK and Switzerland, respectively. At that time, the consensus U.S. GDP growth forecast for 2015 was 2.48%. However, the two banks held differing expectations: HSBC was more optimistic, with a forecast of 2.5%, while UBS was more pessimistic, forecasting 2.3%. At the same time, their loan shares also differed, with HSBC financing 6.72% of the $3.77 billion and UBS financing 4.23%. This example highlights the granularity of our dataset, which enables us to analyze the credit supply decisions of banks with varying macroeconomic expectations within the same loan tranche, while accounting for numerous confounding factors.

4 Macroeconomic Expectation Formation Process

Before conducting the empirical analysis using the loan-level dataset, we examine how global banks form their macroeconomic expectations by performing the tests following Coibion and Gorodnichenko (2015), Bordalo, Gennaioli, Ma, et al. (2020), and Gemmi and Valchev (2026).

First, Coibion and Gorodnichenko (2015) (hereafter CG) derive a test of information rigidity through an identical relationship between the average ex post forecast errors and

the average ex ante forecast revisions across agents from two theoretical rational expectations models with information frictions. The first is the sticky-information model of Mankiw and Reis (2002), in which agents face a fixed cost to acquiring new information, and the degree of information rigidity is captured by the probability of not updating information in each period. The second is the noisy-information model of Woodford (2002) and Sims (2003), where agents cannot observe the true state directly and instead solve a signal extraction problem; in this case, the degree of information rigidity corresponds to the weight placed on prior beliefs. Both models imply that the coefficient from regressing forecast errors on forecast revisions depends solely on the degree of information rigidity. We provide the full theoretical derivation from both models in Appendix Section A2.

Building on their findings, the relationship between ex post *consensus* forecast errors and ex ante *consensus* forecast revisions are the following:

$$x_{t+h} - \overline{F_t x_{t+h}} = c + \beta_{CG}(\overline{F_t x_{t+h}} - \overline{F_{t-1} x_{t+h}}) + \epsilon_t \tag{1}$$

where $\overline{F_t x_{t+h}}$ denotes the mean forecast of the macroeconomic variable x for $t+h$ made at time t, and x_{t+h} is its realization at $t+h$. Thus, $x_{t+h} - \overline{F_t x_{t+h}}$ represents the forecast error, and $\overline{F_t x_{t+h}} - \overline{F_{t-1} x_{t+h}}$ captures the forecast revision between t and $t-1$. If the full information rational expectation (FIRE) hypothesis holds, both the constant term c and the coefficient β should be zero, and no other variables should have additional predictive power for forecast errors conditional on forecast revisions.[11] Importantly, evidence of information rigidities arises if we find $\beta_{CG} > 0$, implying an "under-reaction" of the average forecast. We apply this test using the average forecasts of global banks in our sample, considering both GDP growth and inflation rate forecasts.

Specifically, the forecast revision is computed as the difference in the forecasted level of GDP growth or inflation for the same country-year between the current month and the

[11] The FIRE test in Coibion and Gorodnichenko (2015) assumes rational updating, implying that the test should be conducted using the average across agents, with individual forecast errors remaining unpredictable.

previous month. The forecast error is calculated as the difference between the realized value and the forecast. Following Benhima and Bolliger (2025), we use the first release of GDP growth and inflation for each country-year as published in the April edition of the IMF's World Economic Outlook (WEO) as the realization values.

Next, Bordalo, Gennaioli, Ma, et al. (2020) (hereafter BGMS) test rational expectations by examining the relationship between *individual* forecast errors and *individual* forecast revisions using the following regression:

$$x_{t+h} - F_t^i x_{t+h} = c_i + \beta_{BGMS}(F_t^i x_{t+h} - F_{t-1}^i x_{t+h}) + \epsilon_t^i \tag{2}$$

where i indexes the individual forecaster, and the remaining notation is as defined above. Under rational expectations, we expect $\beta_{BGMS} = 0$, because forecast errors should not be predictable from forecast revisions. By contrast, $\beta_{BGMS} < 0$ indicates overreaction: forecasters revise their expectations too aggressively in response to new information, so revisions tend to overshoot the subsequent realization.

Third, Gemmi and Valchev (2026) propose a test for the presence of strategic incentives in forecasting—namely, that forecasters may strategically overreact to stand out from the crowd—by augmenting the regression with the response of forecast errors to deviations in public signals. The regression specification is as follows:

$$x_{t+h} - F_t^i x_{t+h} = c + \beta_{GV}^1(F_t^i x_{t+h} - F_{t-1}^i x_{t+h}) + \beta_{GV}^2(\overline{F_{t-1}x_{t+h}} - F_{t-1}^i x_{t+h}) + \epsilon_t^i \tag{3}$$

In this test, the lagged consensus forecast, $\overline{F_{t-1}x_{t+h}}$, serves as a proxy for the public signal, and $\overline{F_{t-1}x_{t+h}} - F_{t-1}^i x_{t+h}$ captures an individual's deviation from that public signal (we label this term PI following Gemmi and Valchev (2026)). A negative β_{GV}^1 ($\beta_{GV}^1 < 0$) implies overreaction to idiosyncratic information. A nonzero β_{GV}^2 ($\beta_{GV}^2 \neq 0$) indicates the presence of strategic diversification, and $\beta_{GV}^2 > 0$ suggests relative underreaction to common signals compared with idiosyncratic signals.

We conduct the three tests for both GDP growth and inflation forecasts. Table 2

Table 2: Under- and Over- Reaction Tests

	CG			BGMS			GV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				GDP Growth					
FR	0.319**	0.316**	0.340***	0.061	0.058	0.079	-0.045	-0.022	-0.038
	(0.129)	(0.127)	(0.125)	(0.068)	(0.067)	(0.066)	(0.061)	(0.060)	(0.060)
PI							0.770***	0.765***	0.719***
							(0.070)	(0.070)	(0.075)
Observations	2315	2315	2315	6947	6947	6947	6947	6947	6947
R^2	0.004	0.011	0.049	0.028	0.032	0.068	0.031	0.066	0.084
Forecaster FE	-	-	-	YES	YES	YES	NO	NO	YES
Forecasted Country FE	NO	YES	YES	NO	YES	YES	YES	YES	YES
Horizon FE	NO	NO	YES	NO	NO	YES	NO	YES	YES
				Inflation					
FR	0.099	0.088	0.094	0.070	0.068	0.078	-0.103	-0.093	-0.096
	(0.282)	(0.280)	(0.284)	(0.153)	(0.153)	(0.155)	(0.145)	(0.147)	(0.147)
PI							0.751***	0.748***	0.753***
							(0.087)	(0.087)	(0.091)
Observations	2070	2070	2070	6182	6182	6182	6182	6182	6182
R^2	0.001	0.013	0.018	0.023	0.034	0.039	0.036	0.041	0.063
Forecaster FE	-	-	-	YES	YES	YES	NO	NO	YES
Forecasted Country FE	NO	YES	YES	NO	YES	YES	YES	YES	YES
Horizon FE	NO	NO	YES	NO	NO	YES	NO	YES	YES

Notes: This table reports the results of over- and under-reaction tests using the three approaches proposed by Coibion and Gorodnichenko (2015) (CG), Bordalo, Gennaioli, Ma, et al. (2020) (BGMS), and Gemmi and Valchev (2026) (GV). The dependent variable is the forecast error, defined as the difference between the realized value of the macroeconomic variable and the forecast. Forecast revision (FR) is defined as the change in an individual's forecast from the previous month to the current month. Public information (PI) is measured as an individual forecaster's deviation from public signals, proxied by the lagged consensus forecast. The horizon is the time interval between the month in which the forecast is made and the year-end month in which the macroeconomic variable is realized. Forecaster, forecasted-country, and horizon fixed effects are included as indicated.

reports results under alternative fixed-effects specifications. Columns (1)-(3) provide evidence of information rigidities in the formation of GDP growth expectations as the consensus forecast revisions are significantly and positively associated with consensus forecast errors in GDP growth rates. The estimated coefficient suggests that the probability of updating information—or the weight placed on new information—is approximately 0.74. In contrast, for inflation expectations, the relationship between forecast revisions and forecast errors is statistically insignificant, indicating no clear evidence against the FIRE hypothesis.[12] Columns (4)-(6) show little evidence of over- or under-reaction in

[12]Our results on inflation expectations appear to contrast with prior literature, which typically finds significant information rigidities in the formation of inflation expectations. To reconcile these differences, we extend the CG test to forecasts from other types of institutions included in the Consensus Economics

the individual-level regressions for either GDP or inflation forecasts. One interpretation is that heterogeneous under- and over-weighting of idiosyncratic versus public signals averages out when not separately specified. When we control explicitly for public signals, columns (7)–(9) indicate strategic diversification: forecasters place relatively more weight on idiosyncratic signals than on public signals.

To sum up, GDP growth expectations among banks in our sample display clear information rigidities. By contrast, we find no evidence that their inflation expectations depart from the full-information benchmark. Moreover, for both GDP growth and inflation, we detect a relative overreaction to idiosyncratic signals compared with public signals. We revisit these expectation-formation processes in Section 5.4, where we estimate equations (2) and (3) at the bank level and use the resulting coefficients to capture each bank's tendency to underreact or overreact to aggregate and idiosyncratic information. This allows us to analyze how the heterogeneity in expectation formation across banks shapes the effect of macroeconomic expectations on credit supply.

5 Macroeconomic Expectation and Credit Supply

We now proceed to investigate the relationship between banks' macroeconomic expectations and their credit supply.

5.1 Empirical Specification and Identification

Our baseline specification is

$$Share_{b,i,l,t} = \alpha_0 + \beta Expect_{b,i',t-1} + \alpha_1 Bank_{b,t-1} + \alpha_2 Loan_{b,i',t-1} + \theta_l + \lambda_{b',t} + \eta_{b,i'} + \epsilon_{b,i,l,t} \tag{4}$$

dataset. Figure A3 in the appendix plots the estimated β coefficients from the CG tests across various categories of forecasters, and those for banks are the same as shown in Table 2. We find that the degree of information rigidity among banks in our sample falls between the lower and upper bounds observed across all institution types. Specifically, in the case of inflation expectations, non-bank financial intermediaries, consulting firms, rating and accounting agencies, and universities and research institutes exhibit the most pronounced rigidity, whereas banks, similar to industry associations and non-financial institutions, do not display significant rigidity.

where b, i, l, and t indicate the bank, the borrower firm, the loan tranche, and the month, respectively. Moreover, we use i' and b' to indicate the country where firm i and bank b are located (hereafter borrower-country and bank-country), respectively. The dependent variable $Share_{b,i,l,t}$ is the share of the loan amount that bank b finances in loan tranche l to firm i in month t. The key explanatory variable $Expect_{b,i',t-1}$ is bank b's expectation of the GDP growth rate of borrower country i' surveyed in the previous month.[13] We are mostly interested in the estimate of β. A positive and statistically significant β indicates that, within a given tranche, a bank with more optimistic expectations about the borrower country's economic growth finances a larger share of the loan than its co-lenders.

For control variables, we include a set of bank-level characteristics in $Bank_{b,t-1}$: bank size captured by the natural logarithm of total assets, (reversed) leverage captured by the ratio of equity to total assets, and the funding structure captured by the ratio of depository funding to assets. Since the bank-level variables are only available at the bank-year level from the BankFocus database, we lag these variables by one year. $Loan_{b,i',t-1}$ is the logarithm of the bank's outstanding loans in the borrower country as of the previous month, which captures the lending history and the existing exposure of the bank to the borrower country.

The granularity of our data allows us to saturate the model with various fixed effects. θ_l is the loan tranche fixed effect. As described in Section 3.2, several banks finance the borrower in the same tranche at the same time; the number of banks, total loan amount, borrowing cost, and maturity are common to the tranche, while loan shares

[13] In Figure A4 in the appendix, we report the OLS estimates obtained by including the expectation measure with lags from zero to twelve months, one at a time. The largest and most precisely estimated effect is obtained for the forecast made one month before the syndicated loan. This finding is plausible given that loan origination and approval take time, so banks may not be able to fully incorporate forecasts released in the same month as the loan. Consistent with this interpretation, the coefficient on the contemporaneous forecast is essentially zero and statistically insignificant. The one-month-lagged forecast thus appears to best capture the most recent macroeconomic expectation available at the time of lending. The forecast made two months earlier remains positive and significant, although its effect is smaller, and the estimate drops to zero at a lag of three months. Beyond that horizon, the estimates fluctuate around zero and are insignificant. Taken together, the evidence suggests that lending decisions respond to recent macroeconomic expectations, formed within the preceding one to two months, rather than to expectations formed further in the past. This is also what one would expect if loan officers act on the bank's most recently published forecast.

differ across banks within it. Fixing the tranche therefore absorbs any factor specific to a given borrower in a particular month, including its credit demand, as in Benincasa, Kabas, and Ongena (2026) and in the spirit of Khwaja and Mian (2008), as well as the actual economic fundamentals and any policy changes in the borrower country at that point in time. The estimate of β thus arises from variation across banks within a tranche and captures the credit supply effect. $\lambda_{b',t}$ is the bank country-month fixed effect, which absorbs macroeconomic and financial conditions in the bank's home country, so that we examine the role of expectations about the borrower country given conditions in the bank country. Finally, $\eta_{b,i'}$ is the bank-borrower country fixed effect, which controls for all time-invariant features of a bank's relationship with a country, such as its long-built lending relationships, its specialization or home bias toward the country, and the cultural or legacy proximity between the two countries. With this fixed effect, β is identified from changes over time in a bank's expectation about a country, relative to the other banks in the same tranche, rather than from persistent differences in optimism across banks. In the estimation, we introduce these elements step by step. We first include borrower-month fixed effects together with tranche-level loan terms, namely the number of banks, total loan amount, and maturity, as controls,[14] then replace them with tranche fixed effects, and we add bank fixed effects before specifying the more demanding bank-borrower country fixed effects. Since a bank's expectations about a country are correlated across the loans it extends to that country, we cluster standard errors at the bank-borrower country level.

A causal interpretation of β in Equation (4) requires that, conditional on the control variables and fixed effects, the bank's expectations about a country's macroeconomic performance are independent of other factors influencing its loans to that country. Two main concerns may challenge this assumption. First, reverse causality could be an issue if a bank's larger loan exposure to a country makes it more optimistic (or pessimistic) about the country's economic growth. To address this concern, we use the lagged value of the

[14]The variable of borrowing cost has a large share of missing observations, thus we do not include it in the regression. The main finding still holds when including it in the control variables, which results in a smaller sample, and it is absorbed once the loan tranche fixed effect is included.

bank's expectation and control for its outstanding loan exposure to the borrower country. Additionally, since our dependent variable is the share of a single tranche to a single firm, it is implausible that such a micro-level lending decision shapes a bank's expectation about the macroeconomy of the borrower country. Second, there may be omitted variables that simultaneously affect a bank's expectations about a country and its credit supply to firms in that country. The fixed effects mitigate this concern substantially. Any factor at the borrower-month or tranche level, including credit demand and the country's realized fundamentals, is absorbed by θ_l; any factor at the bank country-month level by $\lambda_{b',t}$; and any time-invariant factor at the bank-borrower country level by $\eta_{b,i'}$. What remains is a confounder that moves over time within a given bank-country pair and differs across the banks in the same tranche, for instance a bank changing its lending strategy toward a country in the same month that it revises its forecast.

We address this residual concern in three ways. First, the coefficient is stable as the fixed effects become more demanding, and the bounding exercise of Oster (2019) reported in Section 5.2 indicates that unobservables would have to be implausibly influential, relative to the observables, to eliminate the effect. Second ,the timing evidence in the appendix shows that the effect is concentrated in the forecast made one month before the loan and absent for forecasts made further in advance, which is difficult to reconcile with a slow-moving bank-country strategy. Third, the subsequent sections show that the effect is driven by participant lenders rather than lead arrangers and is stronger when forecasters disagree, patterns that follow from beliefs mattering for allocation but not from the alternative explanations. These strategies significantly mitigate, though cannot entirely eliminate, concerns about endogeneity.

Finally, another important underlying assumption for our investigation into the impact of macroeconomic expectations on bank credit supply is the consistency of expectations between the forecasters in the research units and the loan decision-makers in the lending units within a bank. In this regard, we highlight two points. First, it is common industry practice for sales teams to refer to the bank's research reports when making rec-

ommendations to clients and addressing questions about macroeconomic expectations. Second, the literature supports the assumption that bank economic projections serve as crucial inputs for lending decisions, mutual fund reallocation, and risk management (D'Acunto, Gao, Liu, et al., 2025; Ma, Paligorova, and Peydro, 2021; Benhima, Bolliger, and Davenport, 2023), and macroeconomic and firm-level news serve as complements in financial markets (Hirshleifer and Sheng, 2022).

5.2 Baseline Results

We now turn to the baseline results. Table 3 presents the estimates, adding control variables and fixed effects step by step. The coefficient on the key variable of interest — the bank's expectation of GDP growth in the borrower's country — is positive and statistically significant in every specification. It is between 2.2 and 2.6 in columns (1)–(5), which compare lending across banks within a borrower-month or a tranche, and falls to about 0.8 in columns (6)–(9) once bank fixed effects or bank-borrower country fixed effects restrict the comparison to variation within a bank's lending to a given country over time. The drop indicates that part of the raw association reflects persistent differences across banks — some banks are both more optimistic and larger banks on average — and the within-bank-country pair estimate in column (9), with the full set of controls and the most saturated fixed effects, is our conservative benchmark: a one-percentage-point more optimistic GDP forecast is associated with an increase in a bank's share of the same tranche by 0.79 percentage points.[15]

The estimated effect is economically meaningful. A one-standard-deviation increase in a bank's growth expectation for a country (1.7 percentage points) is associated with a 1.4 percentage point increase in its share of a tranche to borrowers in that country — 8.3% of the mean share and roughly one-tenth of a standard deviation of shares. With an average tranche of approximately $789 million, this corresponds to about $11 million

[15]Table A13 in the appendix re-estimates the baseline excluding the loans between US banks and US borrowers. The coefficient remains positive and significant in every specification, and the benchmark estimate (0.75) is close to the full-sample value, so the effect is not driven by the US domestic market.

Table 3: Baseline: GDP Growth Expectation and Loan Share

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L.GDP Growth Expectation	2.545***	2.181***	2.183***	2.631***	2.627***	0.818***	0.806***	0.806***	0.789***
	(0.666)	(0.630)	(0.629)	(0.560)	(0.618)	(0.235)	(0.239)	(0.255)	(0.260)
L.Ln(Asset)		0.169	0.171	0.284	0.250	1.264***	1.271***	1.213***	1.178***
		(0.202)	(0.203)	(0.338)	(0.360)	(0.147)	(0.214)	(0.167)	(0.242)
L.Equity/Asset Ratio		0.013	0.014	-0.036	-0.027	-0.045	-0.038	-0.041	-0.038
		(0.052)	(0.052)	(0.092)	(0.101)	(0.060)	(0.060)	(0.065)	(0.065)
L.Deposit/Asset Ratio		-0.032	-0.032	-0.037	-0.037	-0.033	-0.026	-0.033	-0.027
		(0.023)	(0.023)	(0.029)	(0.032)	(0.023)	(0.023)	(0.025)	(0.025)
L.Ln(Outstanding Loans)		2.273***	2.253***	2.202***	2.216***	1.359***	1.196*	1.447***	1.453*
		(0.176)	(0.176)	(0.243)	(0.259)	(0.302)	(0.713)	(0.366)	(0.837)
Number of Banks			-0.320***	-0.313***		-0.318***	-0.318***		
			(0.037)	(0.038)		(0.038)	(0.038)		
Ln(Tranche Amount)			-0.415***	-0.408***		-0.403***	-0.404***		
			(0.091)	(0.094)		(0.095)	(0.095)		
Tranche Maturity			-0.004*	-0.004*		-0.004	-0.004		
			(0.002)	(0.002)		(0.002)	(0.002)		
Observations	25752	25752	25752	25752	25752	25752	25752	25752	25752
R^2	0.718	0.735	0.736	0.746	0.765	0.768	0.769	0.787	0.788
Bank Control	NO	YES	YES	YES	YES	YES	YES	YES	YES
Tranche Control	NO	NO	YES	YES	-	YES	YES	-	-
Borrower × Month FE	YES	YES	YES	YES	-	YES	YES	-	-
Tranche FE	NO	NO	NO	NO	YES	NO	NO	YES	YES
Bank Country × Month FE	NO	NO	NO	YES	YES	YES	YES	YES	YES
Bank FE	NO	NO	NO	NO	-	YES	-	YES	-
Bank × Borrower Country FE	NO	NO	NO	NO	NO	NO	YES	NO	YES

Notes: This table presents the OLS estimates of the baseline specification. The dependent variable is the loan share (in percentage points) funded by a bank in the tranche. The key explanatory variable is the bank's GDP growth expectation for the borrower's country, lagged by one period. The inclusion of control variables and fixed effects is as specified. Standard errors clustered at the bank-borrower-country level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

of additional credit per tranche. A perhaps more relevant yardstick is the dispersion of beliefs within a syndicate: the standard deviation of a bank's forecast around the mean forecast of its co-lenders in the same tranche is 0.22 percentage points, so a one-standard-deviation within-tranche deviation in beliefs reallocates about 0.17 percentage points of each loan from the less to the more optimistic members. Small per contract, this tilt operates on every deal a bank joins and accumulates into the country-level reallocations, which we will document later.

Turning to the control variables, the bank's balance-sheet characteristics play a limited role. Bank size is positively associated with the loan share, but the coefficient is significant only once bank fixed effects are included, meaning that a bank takes larger shares in periods when its own balance sheet is growing rather than that larger banks take larger shares on average. The equity-to-asset and deposit-to-asset ratios enter with

small, statistically insignificant coefficients in all specifications. By contrast, the volume of existing outstanding loans between a bank and a borrower country is positively and significantly associated with its loan share across all specifications, with the coefficient falling by roughly half once bank or bank-borrower country fixed effects absorb the persistent component of lending relationships — underscoring that both the level and the recent build-up of a relationship matter for allocation within a syndicate. Among the tranche characteristics, a bank's share is mechanically lower when the tranche involves more banks or a larger financing amount, while tranche maturity has a small negative coefficient that is only marginally significant or insignificant.

To further address concerns about omitted variables and selection on unobservables, we follow Oster (2019) and compute bounding sets for the coefficient, as well as the degree of selection on unobservables, relative to observables, that would be required to explain the result away. The controlled regression is the benchmark specification of column (9) in Table 3 ($\tilde{R} = 0.788$), so the observables comprise the control variables together with the full set of fixed effects.[16] Table 4 reports the results under different assumptions about R_{max}, the R-squared of a hypothetical regression that also includes the unobservables; δ denotes the proportionality of selection on unobservables relative to observables, and $\tilde{\delta}$ is the value of δ that would drive the estimate to $\beta = 0$ for a given R_{max}.[17] All bounding sets are positive and exclude zero. Since controlling for observables increases the coefficient relative to the regression without controls, our benchmark estimate of 0.789 is the lower bound of every set, with upper bounds between 1.06 (for $R_{max} = 1.15\tilde{R}$) and 1.27 (for $R_{max} = 1$). Correspondingly, $\tilde{\delta}$ is negative, ranging from -1.6 to -3.0: to produce a zero effect of banks' macroeconomic expectations, the unobservables would have to be between 1.6 and 3 times as important as the full set of observables *and* be selected in the opposite direction. We regard such a bias as implausible; if anything, the baseline

[16] Treating the fixed effects as part of the maintained specification rather than as observables, exact Oster bounds and the sensitivity framework of Diegert, Masten, and Poirier (2026) lead to the same conclusion.

[17] Oster (2019) defines δ through $\delta \frac{\sigma_{1X}}{\sigma_1^2} = \frac{\sigma_{2X}}{\sigma_2^2}$, where $\sigma_{iX} = cov(W_i, X)$, $\sigma_i^2 = var(W_i)$, and W_1 and W_2 denote the observables and unobservables, respectively.

estimate understates the effect.

Table 4: Bounding Estimates

R_{max}	Bounding Set	$\tilde{\delta}$ for $\beta = 0$ given R_{max}
$R_{max} = 0.91$ $(1.15\tilde{R})$	[0.789,1.056]	-2.955
$R_{max} = 0.98$ $(1.25\tilde{R})$	[0.789,1.234]	-1.773
$R_{max} = 1.00$ $(1.3\tilde{R})$	[0.789,1.269]	-1.643

Notes: This table presents the bounding estimates following Oster (2019). R_{max} denotes the assumed R-squared from a hypothetical regression that includes unobservable controls. $\tilde{R}$ is the R-squared from the regression including all observable controls, as reported in the last column of Table 3. The bounding set represents the interval estimates for the coefficient of interest in the hypothetical regressions with unobservables. $\tilde{\delta}$ denotes the calculated proportionality of selection between unobservables and observables needed to fully attenuate the effect of the key explanatory variable, i.e., to obtain an estimate of $\beta = 0$, for a given R_{max}.

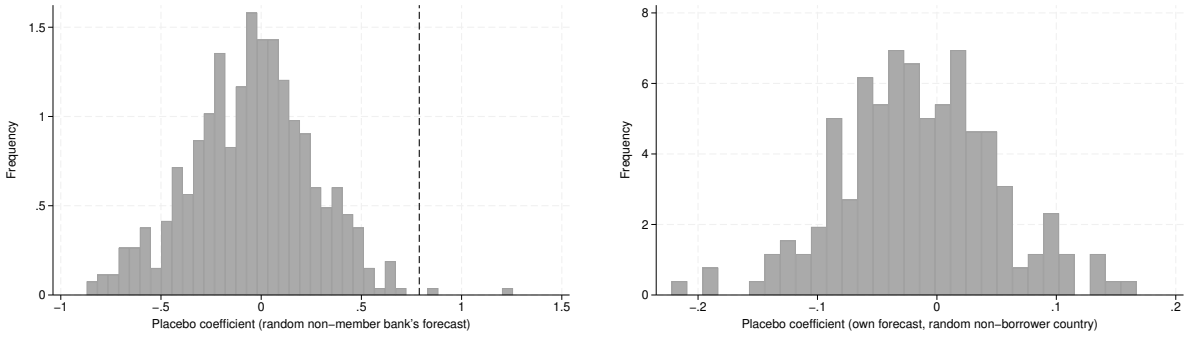
A natural concern is that the bank's GDP forecast for the borrower's country proxies for something else that moves lending, such as conditions in the bank's home market, the bank's overall optimism, or common news about the borrower's country that any market participant observes. The saturated fixed effects in the baseline specification already mitigate this concern; we address it further with falsification tests along the two dimensions of our treatment, replacing the key regressor with the same bank's forecast for the wrong country and with the wrong bank's forecast for the same country.[18]

Panel (a) of Figure 3 implements the "wrong-bank" falsification as a randomization test. For every bank-tranche observation we replace the bank's own forecast with a forecast for the same borrower country and month drawn at random from banks that are not members of the syndicate, keeping the specification, the lag timing, and—by construction—the estimation sample identical to the baseline. Any such forecast embodies the same country-month fundamentals and public news as the bank's own; if the baseline captured common shocks to the borrower's economy rather than the bank's belief, the placebo forecast should explain loan shares equally well. We repeat the draw 500 times and plot the distribution of placebo coefficients. The distribution is centered

[18] A first check horse-races the bank's forecast for the borrower's country against its forecast for its own headquarters country, the natural summary of home-market conditions and loan demand. As Table A12 in the appendix shows, the borrower-country forecast retains its full effect, while the headquarters forecast enters small, negative, and insignificant: what moves a bank's share is its view of the economy the loan is exposed to, not the outlook at home.

at zero, and only 6 of 500 draws exceed the baseline estimate of 0.789 in absolute value, yielding a randomization-inference p-value of 0.014.

Panel (b) of Figure 3 applies the same procedure within bank: we replace the key regressor with the bank's own forecast for a randomly chosen country other than the borrower's, in the same month and at the same lag, and repeat the draw 200 times, as this placebo is mechanically available only for banks forecasting at least two countries. The placebo forecasts carry everything that is common to the bank's forecasting at a point in time—its general optimism, its forecasting style, the quality of its research department—but no information specific to the borrower's country. The resulting distribution is tightly centered at zero: the placebo coefficients have mean -0.02 and standard deviation 0.07, and the most extreme of the 200 draws is less than a third of the baseline estimate. The message is unambiguous: bank-wide sentiment does not move syndicate shares. Together, these exercises indicate that the baseline effect is specific to the match between the forecasting bank and the borrower's country: it is this bank's belief about this economy that drives credit supply.



(a) Random non-member bank's forecast

(b) Own forecast, random non-borrower country

Figure 3: Randomization tests with falsified expectations

Notes: Each panel plots the distribution of placebo coefficients obtained by replacing the bank's GDP growth expectation for the borrower's country with a falsified expectation and re-estimating the baseline specification. Panel (a): a forecast for the same borrower country and month drawn at random from banks outside the syndicate (500 draws, identical sample to the baseline); the dashed line marks the baseline estimate of 0.789. Panel (b): the bank's own forecast for a randomly chosen country other than the borrower's, same month and lag (200 draws); no draw comes close to the baseline estimate.

Another alternative reading of our baseline estimate is strategic volume building: a

bank may take larger shares in a country not because it believes in that economy, but because it seeks to build lending volume and relationships there — for league-table standing, cross-selling, and/or future mandates. Two features of the baseline already restrict this story: the bank-borrower country fixed effects absorb any permanent targeting of particular markets, and the control for the bank's outstanding loan volume in the country absorbs the accumulated stock of such a strategy. What remains is a time-varying volume push, which we test directly by bringing the bank's *previous* loan in the same country into the specification. For each bank-country pair we order loans by month and construct the bank's share in its most recent prior tranche in that country and the GDP growth expectation that prevailed at that loan.[19] Table 5 reports the results. If shares reflected volume momentum, the previous share should carry the explanatory power and the current belief should not: we find the opposite. The share in the previous loan enters small and insignificant, the expectation that accompanied the previous loan has no effect once the current expectation is included, and the current expectation retains its magnitude and significance throughout. It is the bank's belief at the time of signing — not the continuation of past lending — that drives its share in the next loan.

5.3 Robustness Checks

We conduct a series of robustness checks on our baseline results. We first ask whether the growth-expectation effect is distinct from banks' expectations about interest rates, which are likely correlated with expected growth and could directly affect the attractiveness of lending to a country. Table 6 controls for banks' forecasts of the borrower country's 3-month interbank rate and 10-year government bond yield, lagged one month as in the baseline. All columns use the smaller sample with available interest rate forecasts. Columns (1)–(2) confirm the baseline result, with growth-expectation coefficients of 0.97

[19]Repeat lending is nearly universal in our sample (98% of observations, with a median gap of one month between successive loans), so the sample is essentially unchanged. With bank-borrower country fixed effects the coefficient on the lagged share is subject to Nickell (1981)-type attenuation; with on average roughly 150 observations per pair the bias is second order, and the lagged share serves as a control rather than an object of interest.

Table 5: Previous Loan Share and Expectation

	(1) Baseline	(2) Prev. Share	(3) Prev. Expectation	(4) Gap $\leq$ 36m
L.GDP Growth Expectation	0.702***	0.652***	0.598**	0.561**
	(0.259)	(0.238)	(0.248)	(0.253)
Share in Previous Loan, Borrower Country		0.082	0.082	0.086
		(0.059)	(0.059)	(0.060)
GDP Growth Expectation at Previous Loan			0.155	0.088
			(0.123)	(0.132)
Observations	25186	25186	25186	25007
R^2	0.788	0.788	0.788	0.788
Bank Control	YES	YES	YES	YES
Tranche FE	YES	YES	YES	YES
Bank Country × Month FE	YES	YES	YES	YES
Bank × Borrower Country FE	YES	YES	YES	YES

Notes: This table presents the OLS estimates of the baseline specification augmented with the bank's share in its most recent previous loan tranche to the same borrower country and the bank's GDP growth expectation that prevailed at that previous loan. The dependent variable is the loan share (in percentage points) funded by a bank in the tranche. The key explanatory variable is the bank's GDP growth expectation for the borrower's country, lagged by one period. The sample consists of observations for which a previous loan by the same bank to the same borrower country is observed. The inclusion of control variables and fixed effects is as specified. Standard errors clustered at the bank-borrower-country level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

and 0.94. Columns (3)-(6) show that expected short-term rates are positively associated with loan shares, while expected long-term yields are insignificant. Moreover, including all three forecasts jointly leaves the growth-expectation coefficients largely unchanged; short-rate expectations remain positive and significant, and bond-yield expectations remain insignificant. Thus, growth expectations do not merely proxy for banks' interest rate outlook. The positive short-rate coefficient is consistent with syndicated loans being priced over short-term benchmarks, linking higher expected rates to higher expected lending returns.

Second, we verify that the baseline is not driven by mechanical features of syndicate composition, specifically, inherited shares in refinancing. About half of the tranches in our sample are refinancings of existing facilities. Refinancings are a natural place to look for a mechanical explanation of our results: if banks simply roll over their existing commitments, shares would be inherited from the previous syndicate rather than chosen in light of current beliefs, and any association with expectations could reflect the composition of the earlier deal. Table 7 examines this by interacting the expectation measure with a refinancing indicator and by splitting the sample. The effect is clearly present in

Table 6: Robustness Check: Control for Interest Rate Expectation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.GDP Growth Expectation	0.967**	0.942*					0.925*	0.902*
	(0.475)	(0.518)					(0.499)	(0.544)
L.3M Interest Rate Expectation			1.230**	1.244*			1.267**	1.298*
			(0.618)	(0.679)			(0.627)	(0.692)
L.10yr Bond Yield Expectation					-0.101	-0.131	-0.449	-0.483
					(0.340)	(0.354)	(0.314)	(0.327)
Observations	19163	19163	19163	19163	19163	19163	19163	19163
R^2	0.788	0.809	0.788	0.809	0.788	0.809	0.788	0.809
Bank Control	YES	YES	YES	YES	YES	YES	YES	YES
Tranche Control	YES	-	YES	-	YES	-	YES	-
Borrower × Month FE	YES	-	YES	-	YES	-	YES	-
Tranche FE	NO	YES	NO	YES	NO	YES	NO	YES
Bank Country × Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Bank × Borrower Country FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: This table presents the estimates of baseline specification with banks' interest rate expectations as additional explanatory variables. The dependent variable is the loan share (in percentage points) funded by a bank in the tranche. The explanatory variables are the bank's expectations of the borrower country's GDP growth rate, 3-month interbank rate, and 10-year government bond yield, each lagged by one month. The inclusion of control variables and fixed effects is as specified. Standard errors clustered at the bank-borrower-country pair level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

new-money loans: among non-refinancing tranches the coefficient is 0.87 and significant, and in the interaction specifications the effect for non-refinancing loans is 0.95. For refinancings the point estimate is of similar size (0.78) but imprecisely estimated, and the interaction term is negative but statistically insignificant, so we cannot reject that the effect is the same across the two loan types. What matters for our purposes is that the result does not rest on the refinancing segment: a bank's expectations govern its share precisely where shares are set afresh — in newly originated loans — which is inconsistent with the mechanical rollover interpretation.

Third, one may be concerned about a potential mismatch between current-year GDP growth expectations and the maturity structure of the loans, which averages more than four years, as shown in the summary statistics. To address this concern, we separate loans into credit lines and term loans and further classify them by maturity at issuance: loans maturing within three years, between three and five years, and beyond five years. Table 8 reports the results for each loan type. Banks' growth expectations significantly affect both credit lines and term loans. The effect is larger and more precisely estimated for credit lines, with coefficients of about 1.1, than for term loans, where the coefficients

Table 7: Robustness Check: Refinancing and New Loans

	Full Sample		Refinance	Non-Refinance
	(1)	(2)	(3)	(4)
L.GDP Growth Expectation	0.947***	0.950***	0.782	0.870***
	(0.237)	(0.238)	(0.611)	(0.237)
L.GDP Growth Expectation × D(Refinance)	-0.446	-0.518		
	(0.613)	(0.630)		
Observations	25752	25752	14082	11413
R^2	0.787	0.788	0.783	0.764
Bank Control	YES	YES	YES	YES
Tranche FE	YES	YES	YES	YES
Bank Country × Month FE	YES	YES	YES	YES
Bank × Borrower Country FE	NO	YES	YES	YES

Notes: This table presents the OLS estimates of the baseline specification augmented with an interaction term between the bank's GDP growth expectation and a dummy variable indicating that the tranche refinances an existing facility (columns 1 and 2), and estimated separately on refinancing and non-refinancing tranches (columns 3 and 4). The dependent variable is the loan share (in percentage points) funded by a bank in the tranche. The key explanatory variable is the bank's GDP growth expectation for the borrower's country, lagged by one period. The direct effect of the refinancing indicator is absorbed by the tranche fixed effects. The inclusion of control variables and fixed effects is as specified. Standard errors clustered at the bank-borrower-country level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

are about 0.7. Across maturities, the impact of GDP growth expectations declines with loan maturity: it is strongest for short-term loans, smaller for medium-term loans, and becomes statistically insignificant for long-term loans. This pattern suggests that short-term lending is more sensitive to near-term macroeconomic conditions captured by current GDP growth expectations, while for longer maturities repayment prospects depend more on long-run firm fundamentals, reducing the role of contemporaneous expectations.

Table 8: Robustness Checks: Subsamples by Loan Types and Maturity

	Credit Line		Term Loan		Below 3 Yr		Between 3-5 Yr		Above 5 Yr	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
L.GDP Growth Expectation	1.122***	1.116***	0.708*	0.696*	1.332***	1.319***	1.304***	1.290***	-1.792	-1.857
	(0.265)	(0.271)	(0.377)	(0.401)	(0.254)	(0.253)	(0.266)	(0.284)	(1.315)	(1.498)
Observations	12499	12499	12794	12794	7992	7989	12274	12269	4917	4917
R^2	0.800	0.805	0.753	0.770	0.759	0.768	0.797	0.812	0.743	0.764
Bank Control	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Tranche Control	YES	-	YES	-	YES	-	YES	-	YES	-
Borrower × Month FE	YES	-	YES	-	YES	-	YES	-	YES	-
Tranche FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Bank Country × Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank × Borrower Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: This table presents the OLS estimates of the baseline specification, restricted to subsamples of loans by type and maturity at issuance, as indicated in the column titles. The dependent variable is the loan share (in percentage points) funded by a bank in the tranche, and the key explanatory variable is the bank's GDP growth expectation for the borrower's country, lagged by one period. The inclusion of control variables and fixed effects is as specified. Standard errors clustered at the bank-borrower-country level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

Fourth, we account for the role of the bank-firm relationship in shaping the impact of banks' macroeconomic expectations. We identify the first time a bank lends to a firm within the universe of syndicated loan data and construct the relationship length, measured in years since the initial loan, together with a dummy variable indicating whether a loan is the first time the bank lends to the firm.[20] First-time loans account for about 38% of the observations in our sample, and among existing relationships the median length is close to six years. A longer relationship may reflect that the bank has accumulated more firm-specific information, which could either substitute for or complement its assessment of the borrower country's macroeconomic outlook.[21]

We interact each measure with the bank's growth expectation. Table 9 reports the results. Columns (1) and (2) use relationship length on the full sample, columns (3) and (4) use the first-time dummy, and columns (5) and (6) use relationship length on the subsample of existing relationships. Lending relationships matter for the level of credit supply: each additional year of relationship raises the bank's share by about 0.3 percentage points, and a bank lending to the firm for the first time holds a share about 4.4 percentage points smaller than other banks in the same tranche. However, they do not alter the role of macroeconomic expectations. The coefficient on growth expectations remains positive and significant in every column, between 0.68 and 1.00, while the interaction terms with relationship length and with the first-time dummy are small and statistically insignificant. These results indicate that macroeconomic expectations shape credit supply on top of, rather than in place of, the firm-specific information embedded in lending relationships: relationship banks commit more to a given borrower, but their commitments respond to the country outlook as strongly as those of new banks.

[20] Alternatively, we use outstanding loans at the bank-firm level to capture the lending relationship, and outstanding loans at the bank-industry level to capture the bank's lending experience in a given industry. We jointly control for bank-country, bank-industry, and bank-firm outstanding loans, and report the results in Table A14 in the appendix. The main results remain robust, with the effect of outstanding loans at the borrower-firm level being the most pronounced.

[21] Banks learn about countries in the same way. Table A15 in the appendix shows that, conditional on country-by-target-year fixed effects, banks with more than ten years of experience forecasting a country make absolute GDP growth forecast errors about 0.16 percentage points smaller than banks in their first two years, roughly a fifth of the mean error, with a similar pattern for inflation forecasts.

Table 9: Robustness Check: Role of Lending Relationship

	Full Sample				Exclude First-Time Lending	
	(1)	(2)	(3)	(4)	(5)	(6)
L.GDP Growth Expectation	0.902***	0.882***	0.700***	0.684***	0.995***	0.987***
	(0.292)	(0.320)	(0.229)	(0.250)	(0.214)	(0.225)
L.GDP Growth Expectation × Lending Relationship (Yr)	-0.024	-0.024			-0.023	-0.023
	(0.022)	(0.024)			(0.017)	(0.018)
Lending Relationship (Yr)	0.300***	0.294***			0.249***	0.247***
	(0.083)	(0.090)			(0.081)	(0.087)
L.GDP Growth Expectation × First-Time Lending			0.225	0.221		
			(0.284)	(0.305)		
First-Time Lending			-4.449***	-4.421***		
			(1.035)	(1.101)		
Observations	25752	25752	25752	25752	15388	14886
R^2	0.770	0.789	0.772	0.791	0.785	0.792
Bank Control	YES	YES	YES	YES	YES	YES
Tranche Control	YES	-	YES	-	YES	-
Borrower × Month FE	YES	-	YES	-	YES	-
Tranche FE	NO	YES	NO	YES	NO	YES
Bank Country × Month FE	YES	YES	YES	YES	YES	YES
Bank × Borrower Country FE	YES	YES	YES	YES	YES	YES

Notes: This table presents the OLS estimates of the baseline specification, augmented with an interaction term between the bank's GDP growth expectation and the bank-firm lending relationship. The lending relationship is proxied either by the number of years since the bank first lent to the firm or by an indicator for first-time lending. The last two columns are estimated on the subsample in which the bank has already established a prior lending relationship with the firm. The dependent variable is the loan share (in percentage points) funded by a bank in the tranche, and the key explanatory variable is the bank's GDP growth expectation for the borrower's country, lagged by one period. The inclusion of control variables and fixed effects is as specified. Standard errors clustered at the bank-borrower-country level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

Finally, in the baseline analysis, we do not distinguish between the nationality of the bank and the borrower, nor do we account for the currency denomination of the loan tranches. We now explore whether the role of banks' macroeconomic expectations about the borrower's country differs depending on whether the loan is cross-border or denominated in a foreign currency. Specifically, we define a dummy variable, $D(Crossborder)$, which equals one if the bank and borrower are headquartered in different countries. We also define $D(In\ Bank\ Currency)$ and $D(In\ Borrower\ Currency)$ to indicate whether the loan is denominated in the bank's or borrower's domestic currency, respectively. In addition, we use $D(Offshore)$ to indicate that the deal currency is neither the bank's nor the borrower's domestic currency. We then interact these dummy variables with the bank's growth expectations in our baseline specification.

Table 10 presents the results and shows that the belief-lending channel is not a currency or cross-border phenomenon. Interacting the growth expectation with indicators for cross-border lending and for the currency denomination of the tranche, we find no

differential effects: the expectation coefficient is statistically identical across all of these margins, remaining at its baseline value of about 0.8. This uniformity is informative about the mechanism. If the effect reflected currency-mismatch exposure or exchange-rate views dressed up as growth expectations, it should concentrate in cross-border, foreign-currency lending; it does not. Instead, expectations about a country's growth move lending to that country's borrowers regardless of where the bank sits or how the claim is denominated — consistent with the channel operating through the assessment of borrowers' real repayment capacity, with currency risk priced and hedged separately in the contract, much as the inflation results indicate for nominal risk.[22]

Table 10: Cross-border and Cross-currency Lending

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.GDP Growth Expectation	0.801***	0.786***	0.802***	0.776***	1.231***	1.294*	0.799***	0.781***
	(0.241)	(0.261)	(0.254)	(0.275)	(0.428)	(0.757)	(0.240)	(0.261)
L.GDP Growth Expectation × D(Crossborder)	0.158	0.097						
	(0.180)	(0.191)						
L.GDP Growth Expectation × D(In Bank Currency)			0.004	0.014				
			(0.141)	(0.152)				
L.GDP Growth Expectation × D(In Borrower Currency)					-0.447	-0.531		
					(0.415)	(0.793)		
L.GDP Growth Expectation × D(Offshore Currency)							0.142	0.166
							(0.207)	(0.233)
Observations	25752	25752	25752	25752	25752	25752	25752	25752
R^2	0.769	0.788	0.769	0.788	0.769	0.788	0.769	0.788
Bank Control	YES	YES	YES	YES	YES	YES	YES	YES
Tranche Control	YES	-	YES	-	YES	-	YES	-
Borrower × Month FE	YES	-	YES	-	YES	-	YES	-
Tranche FE	NO	YES	NO	YES	NO	YES	NO	YES
Bank Country × Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Bank × Borrower Country FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: This table presents the OLS estimates of the baseline specification augmented with an interaction term between the bank's GDP growth expectation and a dummy variable indicating, respectively, that the bank and borrower are headquartered in different countries (columns 1 and 2), that the tranche is denominated in the bank's domestic currency (columns 3 and 4), in the borrower's domestic currency (columns 5 and 6), or in a currency that is neither (columns 7 and 8). The direct effects of these indicators are absorbed by the fixed effects. The dependent variable is the loan share (in percentage points) funded by a bank in the tranche. The key explanatory variable is the bank's GDP growth expectation for the borrower's country, lagged by one period. The inclusion of control variables and fixed effects is as specified. Standard errors clustered at the bank-borrower-country level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

[22]Banks typically bear little direct exchange-rate risk in cross-border lending: loans are predominantly denominated in major funding currencies in which global banks fund themselves (in our estimation sample, 80 percent of tranches are in U.S. dollars or euros, rising to 87 percent among cross-border loans), so currency mismatch is largely avoided through matched funding; residual mismatches are hedged with foreign exchange swaps and cross-currency basis swaps (see Borio, McCauley, McGuire, et al., 2016; Du, Tepper, and Verdelhan, 2018, on the structure and pricing of these markets). Where loans are instead denominated in the bank's currency, the exchange-rate exposure shifts to the borrower and affects the bank only through borrower credit risk — a component of the repayment-capacity assessment that our growth-expectation measure captures.

5.4 Mechanisms

The baseline establishes that a bank's own growth expectation moves its share. We now ask through which channel. Our working hypothesis is that beliefs matter where they fill an informational gap: a bank's private view of a country can shape its allocation only where it is not already embodied in the information shared by the syndicate. We examine five implications: (1) who acts on beliefs: participants, whose shares are discretionary, rather than lead arrangers, whose shares are set by their role, and on the intensive rather than the extensive margin; (2) when beliefs carry private information: where forecasters disagree; (3) for which borrowers: those whose exposure to the macroeconomy is least salient in the common assessment of the loan; (4) which beliefs transmit: those of banks whose forecasts efficiently incorporate public information; and (5) when a bank can act on its beliefs: beliefs should matter more when the bank's own balance sheet leaves it room to lend.

First, we examine whether lead arrangers behave differently from the other banks with respect to their macroeconomic expectations within a loan tranche. Specifically, we define lead lenders as those whose primary roles are listed as lead arranger or manager in the origination of syndicated loans, and we include an interaction term between the lead lender dummy and the bank's macroeconomic expectation in the baseline specification.[23] Table 11 presents the results. As before, banks' growth expectations have a significantly positive effect, while the interaction term is negative and significant in every column. In the most saturated specifications in columns (8) and (9), the interaction nearly offsets the main effect, so that the implied effect of growth expectations for lead lenders is close to zero. Lead lenders also hold smaller shares than other banks in the same tranche, conditional on bank and tranche characteristics. These results indicate that the within-tranche relation between expectations and loan shares is driven by participant lenders rather than by lead arrangers. One interpretation, consistent with known lending prac-

[23] More precisely, we classify banks as lead lenders if their primary roles are one of the following: co-lead arranger, co-lead manager, lead arranger, lead manager, mandated lead arranger, or senior lead manager.

tices in the syndicated loan market, is that the lead arranger's share is largely determined by its underwriting and monitoring role and by the need to signal commitment to the syndicate, whereas participants are free to scale their commitments according to their own assessment of the borrower country's outlook.

Table 11: Role of Lead Lenders

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L.GDP Growth Expectation × D(Lead Lender)	-0.986***	-0.963***	-0.894***	-0.916***	-0.868***	-0.828***	-0.826***	-0.780***	-0.774***
	(0.248)	(0.256)	(0.232)	(0.217)	(0.230)	(0.213)	(0.213)	(0.251)	(0.251)
L.GDP Growth Expectation	2.649***	2.286***	2.280***	2.743***	2.730***	0.923***	0.908***	0.902***	0.882***
	(0.656)	(0.619)	(0.619)	(0.543)	(0.603)	(0.244)	(0.247)	(0.264)	(0.269)
D(Lead Lender)	-1.651**	-1.361**	-1.543**	-1.708**	-2.125***	-1.672**	-1.752**	-2.094**	-2.200**
	(0.700)	(0.669)	(0.678)	(0.709)	(0.726)	(0.785)	(0.793)	(0.848)	(0.857)
Observations	25752	25752	25752	25752	25752	25752	25752	25752	25752
R^2	0.720	0.737	0.738	0.748	0.767	0.770	0.770	0.789	0.789
Bank Control	NO	YES	YES	YES	YES	YES	YES	YES	YES
Tranche Control	NO	NO	YES	YES	-	YES	YES	-	-
Borrower × Month FE	YES	YES	YES	YES	-	YES	YES	-	-
Tranche FE	NO	NO	NO	NO	YES	NO	NO	YES	YES
Bank Country × Month FE	NO	NO	NO	YES	YES	YES	YES	YES	YES
Bank FE	NO	NO	NO	NO	NO	YES	-	YES	-
Bank × Borrower Country FE	NO	NO	NO	NO	NO	NO	YES	NO	YES

Notes: This table presents the OLS estimates of the specification augmented with a dummy variable indicating whether the bank is a lead lender in the tranche and its interaction with the bank's GDP growth expectation. The dependent variable is the loan share (in percentage points) funded by a bank in the tranche. The key explanatory variable is the bank's GDP growth expectation for the borrower's country, lagged by one period. The sample is restricted to observations with non-missing lender role information. The inclusion of control variables and fixed effects is as specified. Standard errors clustered at the bank-borrower-country level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

A related concern is that the within-tranche relation could arise from how syndicates are formed rather than from how shares are allocated. If the lead arranger invites banks that are optimistic about the borrower country, the syndicate would consist of banks with high expectations even if each bank's share were unrelated to its beliefs. The evidence in Figure A5 in the appendix already speaks against syndicates forming around a lead arranger's optimism, since lead and participant forecasts coincide on average. Consistently, Table A16 in the appendix shows that, within tranches and under the baseline fixed effects, the lead-lender dummy has no explanatory power for a bank's growth expectation.

Now we use a simple numerical exercise to show that belief-based invitation alone cannot generate our result. We consider 100 banks whose forecasts are drawn from a normal distribution with mean 2.1 and standard deviation 1.7, matched to the data, and simulate 1,000 tranches, each with a syndicate of ten banks and a fixed declining

share schedule from 20% to 5%, normalized to sum to 100. We then regress the share on the forecast with tranche fixed effects, the within-tranche design of the paper. Table 12 reports the results under five syndicate formation rules. Under Rule 1, a randomly chosen leader invites the nine banks with the highest forecasts, and shares are then sorted by forecast. Rule 2 uses the same belief-based invitation, but the leader takes the largest share and the invitees follow by forecast rank. Under Rules 3 and 4, invitees are chosen at random, and shares are sorted by forecast either among all members (Rule 3) or among the participants after the leader takes the largest share (Rule 4). Rule 5 randomizes both invitation and shares and serves as a placebo. The coefficient on the forecast is large and positive whenever shares are allocated by beliefs, regardless of how the syndicate is formed, as in Rules 1, 3, and 4. It is zero under Rule 2, even though invitation is belief-based, because the tranche fixed effects absorb the selection of optimistic banks into the syndicate, and the leader, whose belief is average but whose share is the largest, breaks the link between shares and beliefs among the remaining members. It is also zero under the placebo. Only belief-based allocation of shares within the syndicate, not belief-based invitation into it, reproduces a positive within-tranche coefficient. Rule 4, in which the leader's share is fixed and the participants' shares follow their beliefs, is the rule closest to the pattern in Table 11.

The baseline estimates capture the intensive margin: how large a share a bank takes in a syndicate it has joined. We next ask whether optimism also affects *which* syndicates a bank joins. For every tranche in the estimation sample, we define as candidate banks the sample banks that lend to the borrower's country at some point in the sample period and have a forecast for that country in the signing month; the dependent variable equals one if the candidate actually participates (roughly one third do). We estimate a linear probability model through the identical specification ladder as the baseline table, with the same controls and pair-clustered standard errors.

Table 13 shows no detectable effect: the coefficient on the GDP growth expectation is small in every column and never significant at the five percent level, whereas the

Table 12: Simulation of Share Allocation

	(1) Rule 1	(2) Rule 2	(3) Rule 3	(4) Rule 4	(5) Rule 5
Forecast	2.450***	-0.004	2.198***	1.817***	0.042*
	(0.034)	(0.025)	(0.017)	(0.019)	(0.025)
Observations	10000	10000	10000	10000	10000
R^2	0.606	0.000	0.868	0.573	0.000
Tranche FE	YES	YES	YES	YES	YES

Notes: This table presents OLS estimates from simulated data. There are 100 banks whose forecasts are drawn from a normal distribution with mean 2.1 and standard deviation 1.7. For each of five syndicate formation rules, 1,000 tranches are simulated, each with a syndicate of ten banks that receive a fixed declining share schedule from 20% to 5%, normalized to sum to 100. Rule 1: a randomly chosen leader invites the nine banks with the highest forecasts and shares are sorted by forecast. Rule 2: the same invitation as Rule 1, but the leader takes the largest share and the invitees follow by forecast rank. Rule 3: invitees are random and shares are sorted by forecast. Rule 4: invitees are random, the leader takes the largest share, and the other members' shares are sorted by forecast. Rule 5: invitees and shares are both random. The dependent variable is the simulated share and the explanatory variable is the simulated forecast; all regressions include tranche fixed effects. Standard errors clustered at the tranche level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

intensive margin survives the same ladder throughout. Expectations govern how much a bank lends within a syndicate, not whether it enters one. This is consistent with the structure of syndicated lending — composition is set by lead arrangers along existing relationships, while each member's share reflects its own willingness to lend — and with the simulation evidence, where observed shares are reproduced by belief-driven allocation within syndicates rather than selection into them.

Table 13: Extensive Margin

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L.GDP Growth Expectation	0.036	0.029	0.029	0.026	0.026	0.015	0.021*	0.015	0.021
	(0.050)	(0.021)	(0.021)	(0.019)	(0.021)	(0.012)	(0.013)	(0.014)	(0.014)
Observations	49760	49760	49760	49760	49760	49760	49760	49760	49760
R^2	0.112	0.388	0.402	0.500	0.544	0.519	0.527	0.563	0.572
Bank Control	NO	YES	YES	YES	YES	YES	YES	YES	YES
Tranche Control	NO	NO	YES	YES	-	YES	YES	-	-
Borrower × Month FE	YES	YES	YES	YES	-	YES	YES	-	-
Tranche FE	NO	NO	NO	NO	YES	NO	NO	YES	YES
Bank Country × Month FE	NO	NO	NO	YES	YES	YES	YES	YES	YES
Bank FE	NO	NO	NO	NO	NO	YES	-	YES	-
Bank × Borrower Country FE	NO	NO	NO	NO	NO	NO	YES	NO	YES

Notes: This table presents linear probability model estimates of the extensive margin of lending. For every tranche in the baseline estimation sample, candidate banks are the sample banks that lend to the borrower's country at some point in the sample period and report a forecast for that country in the signing month. The dependent variable equals one if the candidate bank participates in the tranche and zero otherwise. The key explanatory variable is the bank's GDP growth expectation for the borrower's country, lagged by one period. All columns use the same sample of bank-tranche observations. The inclusion of control variables and fixed effects is as specified. Standard errors clustered at the bank-borrower-country level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

Second, we examine whether the impact of macroeconomic expectations varies with the degree of disagreement among forecasters. We use three measures of disagreement about the borrower country's current-year GDP growth, each computed from forecasts made in the month before the loan: the standard deviation across all forecasters in the CE survey (overall SD), the standard deviation across the banks in our sample (in-sample SD), and the standard deviation across the banks participating in the same tranche (within-tranche SD). The first two vary at the borrower country-month level and the third at the tranche level, so their direct effects are absorbed by the borrower-by-month or tranche fixed effects, and we interact each measure with the bank's own expectation.

Table 14 presents the results. For all three measures and across fixed-effect specifications, the interaction term is positive and, with one exception, statistically significant, while the coefficient on the expectation itself, which captures the effect when forecasters fully agree, is insignificant. The effect of a bank's growth expectation on its credit supply is therefore increasing in the degree of disagreement. The magnitudes are economically meaningful: a one-standard-deviation increase in disagreement raises the coefficient on growth expectations by about 0.27 for the overall SD, 0.20 for the in-sample SD, and 0.19 for the within-tranche SD, between a quarter and two-fifths of the baseline estimate. This pattern is intuitive. Our identification relies on differences between a bank's expectation and those of the other banks in the same tranche. When forecasters agree, a bank's own forecast is close to the consensus, which is absorbed by the fixed effects, and there is little scope for its beliefs to shape its lending. When forecasters disagree, a bank's forecast carries more information that is specific to the bank, and its lending decisions respond to it more strongly. The finding also indicates that macroeconomic expectations matter most for credit supply precisely when the macroeconomic outlook is most uncertain. Interestingly, this contrasts with Hoerdahl, Kısacıkoğlu, and Xia (2026), who find that greater forecast disagreement dampens the response of the yield curve to macroeconomic news: in prices, disagreement averages out across investors, whereas in a syndicate, where each bank sets its own share, it is exactly what gives individual beliefs

room to operate.

Table 14: Role of Disagreement

	Overall SD			In Sample SD			Within Tranche SD		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L.GDP Growth Expectation × SD	1.564*	1.675*	1.598	1.171***	1.221***	1.185**	0.878***	0.845***	0.827***
	(0.933)	(0.960)	(1.007)	(0.424)	(0.432)	(0.457)	(0.257)	(0.300)	(0.315)
L.GDP Growth Expectation	-0.515	-0.606	-0.561	-0.437	-0.486	-0.470	-0.493	-0.438	-0.435
	(1.048)	(1.111)	(1.130)	(0.798)	(0.847)	(0.857)	(0.751)	(0.832)	(0.840)
Observations	25752	25752	25752	25752	25752	25752	25752	25752	25752
R^2	0.769	0.787	0.788	0.769	0.787	0.788	0.769	0.787	0.788
Bank Control	YES	YES	YES	YES	YES	YES	YES	YES	YES
Tranche Control	YES	-	-	YES	-	-	YES	-	-
Borrower × Month FE	YES	-	-	YES	-	-	YES	-	-
Tranche FE	NO	YES	YES	NO	YES	YES	NO	YES	YES
Bank Country × Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	-	YES	-	-	YES	-	-	YES	-
Bank × Borrower Country FE	YES	NO	YES	YES	NO	YES	YES	NO	YES

Notes: This table presents the OLS estimates of the baseline specification augmented with an interaction term between the bank's GDP growth expectation and a measure of disagreement among forecasters. Disagreement is measured by the standard deviation of one-period-lagged current-year GDP growth forecasts for the borrower's country across all forecasters in the Consensus Economics survey (columns 1 to 3), across the banks in our sample (columns 4 to 6), and across the banks in the same tranche (columns 7 to 9). The direct effect of each measure is absorbed by the fixed effects. The dependent variable is the loan share (in percentage points) funded by a bank in the tranche. The key explanatory variable is the bank's GDP growth expectation for the borrower's country, lagged by one period. The inclusion of control variables and fixed effects is as specified. Standard errors clustered at the bank-borrower-country level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

Third, if banks' growth expectations shape credit supply because they inform the assessment of borrowers' repayment prospects, the strength of this channel may depend on how closely a borrower's fortunes are tied to the aggregate economy. We therefore examine whether the effect of growth expectations varies with the cyclicality of the borrower's sector. We assign each borrower to one of the 49 Fama-French industries using its primary SIC code in DealScan and construct three measures of sector cyclicality from the corresponding industry portfolio returns. The first is a GDP beta, obtained by regressing the calendar-year return of each industry portfolio on next year's U.S. real GDP growth; using next year's growth reflects that stock returns lead real activity. The second is a CAPM beta, obtained by regressing monthly industry excess returns on the market excess return. Both are estimated over 1950 to 1992, before the start of our loan sample, so that they are predetermined with respect to the lending decisions we study.[24] Since

[24]The two pre-sample measures are positively correlated across industries. The most cyclical industries by GDP beta include aircraft, restaurants, automobiles, textiles, and transportation; the least cyclical

industry betas may drift over three decades, the third measure is a time-varying CAPM beta estimated over a rolling 120-month window ending in the month before the loan is signed, so that it uses only information available at the time of lending. Each measure is standardized, the two pre-sample betas across the estimation sample and the rolling beta across industries within each month. Because the borrower's industry is fixed within a tranche, the direct effect of cyclicality is absorbed by the tranche fixed effects, and we identify its role through the interaction with the bank's expectation and through separate estimates for borrowers above and below the median of each measure.

Table 15 reports the results. Columns (1) to (3) show that the interaction between growth expectations and sector cyclicality is negative and statistically significant for all three measures. Evaluated at the mean level of cyclicality, the effect of growth expectations is about 0.9, close to the baseline estimate, but it is roughly twice as large for a borrower one standard deviation below the mean and close to zero for a borrower one standard deviation above it. The split-sample estimates in columns (4) to (9) confirm this pattern: among borrowers in less cyclical sectors, the coefficient on growth expectations is significant and ranges from 1.26 to 1.61, whereas among borrowers in more cyclical sectors it ranges from 0.31 to 0.62 and is statistically insignificant. The effect of macroeconomic expectations on credit supply is thus concentrated among borrowers whose performance is least sensitive to the aggregate cycle.

This is consistent with our interpretation that banks' own macroeconomic expectations matter most where they fill an informational gap. For highly cyclical borrowers, the mapping from aggregate conditions to borrower performance is well understood and largely reflected in the loan terms shared by all syndicate members, leaving little room for a bank's own view to shift its share. For less cyclical borrowers, the country outlook still bears on repayment but is less salient in the common assessment of the loan, so the bank's private macroeconomic view has more room to shape its participation decision.

include precious metals, tobacco, telecommunications, pharmaceuticals, food, and utilities. The GDP beta is unavailable for the healthcare industry, whose portfolio has only 23 complete pre-sample years, below the 25-year minimum we impose; borrowers in this industry are excluded from the estimation.

The same logic underlies our earlier findings that the effect is stronger when forecasters disagree and that it operates through participant lenders rather than lead arrangers.

Table 15: Sector Cyclicality and the Effect of Growth Expectations

	(1) Pre-Sample GDP	(2) Pre-Sample CAPM	(3) Rolling Sample CAPM	(4) High GDP	(5) Low GDP	(6) High CAPM Pre	(7) Low CAPM Pre	(8) High CAPM Rolling	(9) Low CAPM Rolling
L.GDP Growth Expectation	0.902***	0.919***	0.915***	0.369	1.437**	0.306	1.608***	0.621	1.259***
	(0.290)	(0.296)	(0.298)	(0.293)	(0.596)	(0.465)	(0.461)	(0.418)	(0.309)
L.GDP Growth Expectation × Cyclicality Beta	-0.669**	-0.908***	-1.096***						
	(0.278)	(0.177)	(0.220)						
Observations	24936	24936	24936	12051	12641	12293	12401	12338	12398
R^2	0.789	0.789	0.789	0.787	0.793	0.781	0.800	0.778	0.806
Bank Control	YES	YES	YES	YES	YES	YES	YES	YES	YES
Tranche FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank Country × Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank × Borrower Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: This table presents OLS estimates of the baseline specification augmented with an interaction between the bank's GDP growth expectation and the cyclicality of the borrower's sector, and separate estimates for borrowers above and below the median of each cyclicality measure. Borrowers are assigned to the 49 Fama-French industries by SIC code. The GDP beta is the coefficient from regressing the calendar-year industry portfolio return on next year's U.S. real GDP growth, and the CAPM pre-sample beta is the coefficient from regressing monthly industry excess returns on the market excess return, both estimated over 1950 to 1992. The CAPM rolling beta is estimated over a 120-month window ending in the month before loan signing. The pre-sample betas are standardized across the estimation sample and the rolling beta across industries within each month. The direct effect of cyclicality is absorbed by the tranche fixed effects. The dependent variable is the loan share (in percentage points) funded by a bank in the tranche, and the key explanatory variable is the bank's GDP growth expectation for the borrower's country, lagged by one month. The inclusion of control variables and fixed effects is as specified. Standard errors clustered at the bank-borrower-country pair level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

Fourth, as described in Section 4, we measure the extent to which forecasters react to new information by examining the relationship between forecast errors and forecast revisions. While the CG measure of information rigidity is defined at the level of the consensus forecast, the BGMS and GV specifications can be implemented forecaster by forecaster. Specifically, we estimate Equations (2) and (3) separately for each bank b and obtain bank-specific coefficients β^b_{BGMS}, β^{b1}_{GV}, and β^{b2}_{GV}.[25] We then interact these coefficients with each bank's GDP growth forecast to examine whether the sensitivity of lending to expectations differs across banks with different degrees of overreaction or underreaction. In particular, we test whether banks that react more strongly to news in forecast formation also exhibit a stronger lending response to their own forecasts.

[25] We characterize banks' expectation formation through these coefficients rather than through realized forecast accuracy. We can measure the bank's past forecast accuracy by the mean squared forecast error (MSFE) of the bank's past GDP forecasts for the borrower's country. However, the relative accuracy is essentially transitory in our data — the year-over-year correlation of a bank's accuracy rank within a country is below 0.1 — so any window of past errors carries little information about current skill. The expectation-formation coefficients, by contrast, are estimated from the bank's entire forecast history under an explicit model of belief updating, and deliver systematic heterogeneity.

To recall, a negative β^b_{BGMS} indicates that a bank overreacts to news, in the sense that upward forecast revisions are followed by realizations that fall short of the forecast. Thus, a more negative β^b_{BGMS} corresponds to stronger overreaction to news. In the GV framework, β^{b1}_{GV} captures the extent to which a forecaster overreacts to idiosyncratic information, with a more negative β^{b1}_{GV} indicating stronger overweighting of idiosyncratic signals. Meanwhile, β^{b2}_{GV} captures the degree to which a forecaster underreacts to public information relative to idiosyncratic information, such that a more positive β^{b2}_{GV} indicates a stronger underweighting of common signals.

We are interested in the interaction between banks' GDP growth forecasts and these three demeaned bank-specific β coefficients. Because these are time-invariant bank characteristics estimated with sampling noise, their interactions are identified from cross-bank variation; we therefore estimate these specifications with bank country-borrower country pair fixed effects, together with tranche (or borrower-month) and bank country-month fixed effects, which preserve that variation, rather than the fully saturated bank-borrower country structure of the baseline, under which the interactions attenuate toward zero and lose significance, as measurement error in the estimated coefficients is amplified by the within-transformation. A negative interaction coefficient for β^b_{BGMS} implies that banks that overreact more strongly in forecast formation transmit their beliefs more aggressively into lending. Likewise, a negative interaction coefficient for β^{b1}_{GV} implies that banks that place greater weight on idiosyncratic information exhibit a stronger lending response to their own forecasts. A negative interaction coefficient for β^{b2}_{GV} would suggest that banks that underweight public information more strongly respond less strongly to their own forecasts in their lending decisions. However, the sign of this last interaction is theoretically ambiguous: conviction in private information could amplify the response, while failure to incorporate public information degrades the forecast as a measure of operative beliefs.

Table 16 reports the results. For the GV specification, we present results that interact banks' forecasts separately with β^{b1}_{GV}, and β^{b2}_{GV}, as well as a specification that includes

Table 16: Heterogeneous Effects Across Banks' Under- and Over-reaction

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.GDP Growth Expectation	2.734***	2.722***	2.773***	2.763***	2.725***	2.714***	2.788***	2.778***
	(0.584)	(0.641)	(0.600)	(0.659)	(0.551)	(0.604)	(0.621)	(0.682)
L.GDP Growth Expectation × β_{BGMS}	-0.360	-0.370						
	(0.396)	(0.427)						
L.GDP Growth Expectation × β^1_{GV}			-0.336	-0.351			-0.564	-0.573
			(0.445)	(0.481)			(0.441)	(0.478)
L.GDP Growth Expectation × β^2_{GV}					-0.216*	-0.208*	-0.277**	-0.270*
					(0.111)	(0.122)	(0.126)	(0.138)
Observations	24067	24067	24067	24067	24067	24067	24067	24067
R^2	0.743	0.761	0.743	0.761	0.743	0.761	0.743	0.762
Bank Control	YES	YES	YES	YES	YES	YES	YES	YES
Tranche Control	YES	-	YES	-	YES	-	YES	-
Borrower × Month FE	YES	-	YES	-	YES	-	YES	-
Tranche FE	NO	YES	NO	YES	NO	YES	NO	YES
Bank Country × Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Bank Country-Borrower Country Pair FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: This table presents the OLS estimates of the baseline specification augmented with interaction terms between the bank's GDP growth expectation and bank-specific measures of expectation formation. β_{BGMS} is the bank-level coefficient from equation (2), and β^1_{GV} and β^2_{GV} are the bank-level coefficients from equation (3), each estimated from the bank's full history of GDP growth forecasts, winsorized at the 1st and 99th percentiles, and demeaned. Because these measures are time-invariant bank characteristics, the specifications include bank country-borrower country pair fixed effects rather than bank-borrower country fixed effects. The dependent variable is the loan share (in percentage points) funded by a bank in the tranche. The key explanatory variable is the bank's GDP growth expectation for the borrower's country, lagged by one period. The inclusion of control variables and fixed effects is as specified. Standard errors clustered at the bank-borrower-country level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

both interaction terms jointly. First, the coefficient on the bank's own GDP forecast remains positive and statistically significant across all specifications, again confirming the baseline finding that banks with more optimistic macroeconomic expectations supply more credit. Second, the results point to the use of public information, rather than over- or underreaction per se, as the margin of expectation formation that matters for lending. The interactions with the overreaction coefficients carry the hypothesized negative signs — banks that overreact to news (β_{BGMS}) or overweight idiosyncratic signals (β^1_{GV}) display somewhat stronger lending responses to their own forecasts — but neither is statistically significant. The informative coefficient is the interaction with β^2_{GV}, which is negative and significant across specifications, implying that lending responds less to the stated forecasts of banks that underweight common signals. We interpret this as an information-quality result: a forecaster with a high β^2_{GV} systematically fails to incorporate publicly available information, so its forecast errors are predictable and its stated forecast is a noisier measure of the assessment that actually guides its lending; the belief-lending pass-

through is accordingly strongest for the banks whose expectations efficiently absorb public information. Quantitatively, a one-standard-deviation higher β^2_{GV} reduces the sensitivity of the loan share to the forecast by 0.23 percentage points, roughly 8 percent of the effect for a bank with average expectation-formation behavior. Taken together, these results indicate that expectations transmit into credit regardless of a bank's forecasting skill, but transmit most faithfully when the stated forecast is an undistorted expression of the bank's information set.

Fifth, we ask whether a bank's ability to act on its beliefs depends on the state of its own balance sheet. A bank's characteristics vary for two distinct reasons, persistent differences across banks and movements in a given bank's balance sheet over time, and the two may bear differently on how beliefs are transmitted to lending. We therefore decompose each characteristic into the bank's deviation from its own sample mean (within-bank) and that mean itself (between-bank), both standardized, and interact the expectation with each component. Table 17 reports the results for size, the equity-to-asset ratio, the deposit-to-asset ratio, and the Tier 1 capital ratio, together with a composite strength index that averages the within-bank components of the equity and deposit ratios. Because the between-bank component is a time-invariant bank trait, we use the bank country-borrower country pair fixed effects as in Table 16, with borrower-month fixed effects and tranche controls in the odd-numbered columns and tranche fixed effects in the even-numbered columns.

The results are uniform across the four characteristics. The between-bank interactions are small and insignificant in every column: banks that are persistently larger, better capitalized, or more deposit-funded than their peers do not respond differently to their expectations. The within-bank interactions are positive and significant throughout: when a bank's balance sheet is stronger than its own norm, its lending responds more to its expectations. A one-standard-deviation improvement relative to the bank's own average, raises the coefficient on growth expectations by between 0.17 and 0.60, and a one-standard-deviation increase in the strength index raises it by 0.64, roughly a quar-

Table 17: Balance-Sheet Capacity and the Effect of Growth Expectations

	Size		Equity/Asset		Deposit/Asset		Tier 1 Ratio		Strength Index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
L.GDP Growth Expectation	1.595***	1.572***	2.621***	2.613***	2.489***	2.481***	1.289**	1.318**	2.514***	2.513***
	(0.372)	(0.393)	(0.621)	(0.686)	(0.330)	(0.364)	(0.548)	(0.598)	(0.554)	(0.610)
L.GDP Growth Expectation × Size, within-bank	0.452***	0.453***								
	(0.158)	(0.171)								
L.GDP Growth Expectation × Size, between-bank	0.010	0.020								
	(0.289)	(0.311)								
L.GDP Growth Expectation × Equity/Asset, within-bank			0.541**	0.543*						
			(0.257)	(0.277)						
L.GDP Growth Expectation × Equity/Asset, between-bank			0.182	0.173						
			(0.199)	(0.220)						
L.GDP Growth Expectation × Deposit/Asset, within-bank					0.169***	0.167**				
					(0.065)	(0.072)				
L.GDP Growth Expectation × Deposit/Asset, between-bank					0.204	0.209				
					(0.244)	(0.267)				
L.GDP Growth Expectation × Tier 1 Ratio, within-bank							0.595**	0.592**		
							(0.246)	(0.269)		
L.GDP Growth Expectation × Tier 1 Ratio, between-bank							-0.008	-0.010		
							(0.125)	(0.137)		
L.GDP Growth Expectation × Balance-Sheet Strength Index, within-bank									0.637***	0.636***
									(0.185)	(0.202)
Observations	25752	25752	25752	25752	25752	25752	19160	18450	25752	25752
R^2	0.752	0.771	0.747	0.766	0.747	0.766	0.781	0.792	0.747	0.766
Bank Control	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Tranche Control	YES	-	YES	-	YES	-	YES	-	YES	-
Borrower × Month FE	YES	-	YES	-	YES	-	YES	-	YES	-
Tranche FE	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Bank Country × Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank Country-Borrower Country Pair FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: This table presents the OLS estimates of the baseline specification augmented with interaction terms between the bank's GDP growth expectation and a bank characteristic decomposed into its within-bank and between-bank components. The within-bank component is the characteristic minus the bank's mean over the sample period, and the between-bank component is that mean; both are standardized. The characteristics are the natural logarithm of total assets, the equity-to-asset ratio, the deposit-to-asset ratio, and the Tier 1 capital ratio, each lagged by one year. The balance-sheet strength index is the average of the within-bank components of the equity-to-asset and deposit-to-asset ratios. The dependent variable is the loan share (in percentage points) funded by a bank in the tranche. The key explanatory variable is the bank's GDP growth expectation for the borrower's country, lagged by one period. The inclusion of control variables and fixed effects is as specified. Standard errors clustered at the bank-borrower-country level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

ter of its level for a bank at its own average. Macroeconomic beliefs thus translate into credit most strongly when the bank has the balance-sheet capacity to act on them. This mirrors, on the bank's side, the finding in Section 6 that macroprudential tightening in the borrower country interrupts the transmission: in both cases, it is the slack available to the bank, rather than the level of its beliefs, that determines how far optimism reaches credit supply.

5.5 From Syndicate Shares to Bank Portfolios and Aggregate Credit

The within-tranche design treats each loan in isolation. If a bank's lending capacity is finite, optimism about one country should not only raise its lending there but also

crowd out its lending elsewhere, so that a bank's share in a tranche depends on the opportunities it perceives in its other markets. We test this directly by augmenting the baseline specification with the bank's *outside option*: a weighted average of the GDP growth expectations it holds for the other countries in which it has outstanding syndicated loans. Three measurement choices matter. First, trend growth differs across countries, so an index of forecast levels would be higher for banks whose portfolios lie in faster-growing economies regardless of news; we therefore measure each country's forecast relative to the time-series average of the Consensus forecast for that country over the sample period, so that the index captures abnormal expected growth in the bank's other markets.[26] Second, weights that move with the bank's current exposure would let the index change with the bank's country mix as well as with its forecasts, and the country mix itself responds to beliefs; we therefore hold the weights fixed, either at the bank's average exposure shares over the sample period or at its shares at the end of 1992, before the sample begins, so that the index varies only with forecasts. Third, Consensus Economics collects forecasts country by country, and a bank does not necessarily forecast every country in which it lends. Where the bank publishes no forecast for one of its other markets, we use the Consensus mean forecast for that country, which lets the index cover the full sample.[27]

Table 18 reports the results using different fixed weights.[28] Two findings stand out. First, the own-country coefficient is unaffected by the outside option in every column, at 0.77 to 0.83 against 0.79 in the baseline. Second, the outside option enters negatively in every column, as capacity constraints predict: between -1.06 and -1.11 with sample-average weights and between -0.54 and -0.56 with pre-sample weights. Taking the more conservative pre-sample estimates, a one-standard-deviation improvement in abnormal expected growth in the bank's other markets lowers its share by about half as much as an

[26] The own-country expectation needs no such adjustment, because the bank-borrower country fixed effects absorb the level of expected growth in each country.

[27] The index is a leave-out average over the 25 countries covered by the individual Consensus forecasts, with the borrower's country excluded.

[28] For banks with no outstanding loans at the end of 1992, the weights are the shares in the first month with positive exposure. The last four columns lose observations for which the bank has no outstanding loans in any other Consensus country at the weight date.

Table 18: Outside Options and Reallocation Across Countries

	Fixed Weight-Average				Fixed Weight-Pre 1992			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.GDP Growth Expectation	0.829***	0.817***	0.816***	0.799***	0.794***	0.779***	0.789***	0.772***
	(0.235)	(0.239)	(0.256)	(0.262)	(0.245)	(0.249)	(0.265)	(0.269)
L.Outside Option	-1.103*	-1.113*	-1.060*	-1.075*	-0.539*	-0.540*	-0.555*	-0.552*
	(0.580)	(0.577)	(0.627)	(0.624)	(0.292)	(0.297)	(0.297)	(0.302)
Observations	25740	25740	25740	25740	24790	24790	24717	24717
R^2	0.768	0.769	0.787	0.788	0.769	0.769	0.787	0.788
p-value (Own + Outside Option = 0)	0.626	0.594	0.685	0.642	0.449	0.479	0.498	0.525
Bank Control	YES	YES	YES	YES	YES	YES	YES	YES
Tranche Control	YES	YES	-	-	YES	YES	-	-
Borrower × Month FE	YES	YES	-	-	YES	YES	-	-
Tranche FE	NO	NO	YES	YES	NO	NO	YES	YES
Bank Country × Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	-	YES	-	YES	-	YES	-
Bank × Borrower Country FE	NO	YES	NO	YES	NO	YES	NO	YES

Notes: This table presents OLS estimates of the baseline specification augmented with the bank's outside option. The dependent variable is the loan share (in percentage points) funded by a bank in the tranche. The key explanatory variable is the bank's GDP growth expectation for the borrower's country, lagged by one period. The outside option is the weighted average of the bank's GDP growth expectations, lagged by one period, for the other countries covered by Consensus Economics, using the bank's own forecast where it publishes one and the Consensus mean forecast for the country otherwise; each country's expectation is measured relative to the time-series average of the Consensus forecast for that country over the sample period. In columns (1)–(4) each country is weighted by the bank's average share of outstanding loans in it over the sample period; in columns (5)–(8) by its share at the end of 1992, or in the first month with positive outstanding loans for banks without exposure at that date. The row *p-value (Own + Outside Option = 0)* reports the test that the coefficients on the own expectation and the outside option sum to zero. The inclusion of control variables and fixed effects is as specified. Standard errors clustered at the bank-borrower-country level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

equal improvement in its expectation for the borrower's country raises it; with sample-average weights the two effects are of similar size. The row below the coefficients tests whether the two effects offset one for one, as they would if reallocation were zero-sum at the bank level: the test does not reject a one-for-one offset in any column, while the absence of crowding out is rejected only at the 10% level. We read the evidence as pointing to partial crowding out: better opportunities elsewhere reduce the share a bank takes of a given loan, while the bank's own view of the borrower's country remains the dominant margin.

Finally, we aggregate the loan-level data to the bank-country level by summing each bank's newly originated loans to all firms within a given country for each month.[29] This

[29] Alternatively, we conduct a bank-level analysis to examine the relationship between banks' macroeconomic expectations and aggregate lending. Using bank-year data, we construct each bank's domestic GDP growth expectation as the annual average of its monthly forecasts for the country in which it is headquartered. The key explanatory variable is the lagged forecast of GDP growth, and the dependent variable is either the loan-to-asset ratio or the logarithm of total loans. We control for standard bank characteristics, including size, equity-to-asset ratio, deposit-to-asset ratio, and profitability. Table

allows us to construct bank lending measures that match the granularity of banks' macroeconomic expectations for that country. We then revise the baseline specification and estimate the following equation:

$$LoanTerm_{b,c,t} = \alpha_0 + \beta Expect_{b,c,t-1} + \alpha_1 Bank_{b,t-1} + \alpha_2 Loan_{b,c,t} + \delta_{c,t} + \lambda_{b',t} + \eta_{b',c} + \epsilon_{b,c,t} \tag{5}$$

Here, b, c, and t denote the bank, borrower country, and month, respectively, and b' denotes the bank country. By aggregating loan-level data and leveraging variation in loan terms across tranches, we are able to examine alternative lending terms in addition to loan shares as dependent variables. Specifically, we define loan shares as the fraction of total loans extended to country c in month t that is supplied by bank b. We also use the natural logarithm of the total loan amount. Additionally, we compute the amount-weighted average borrowing cost measured by the basis points above the risk-free rate and maturity measured as the number of months for all loans supplied by bank b to country c in month t. $Bank_{b,t-1}$ captures lagged bank-level characteristics. $Loan_{b,c,t}$ includes the bank's lagged outstanding loans to the country and, in the most saturated specifications, the contemporaneous lending terms other than the dependent variable, so that the estimated effect on one lending term is conditional on the others; since the lending terms are jointly determined, we also report specifications without these controls, which yield similar estimates. Consistent with the baseline analysis, $\delta_{c,t}$ denotes borrower country-month fixed effects, which help account for credit demand. $\lambda_{b',t}$ and $\eta_{b',c}$ represent bank country-month and bank country-borrower country pair fixed effects, respectively.

Table 19 presents the results. The micro-level allocations aggregate: at the bank-country level, banks with more optimistic growth expectations for a country take a larger share of the credit extended to that country, lend larger amounts, and originate loans at higher average spreads. The coefficients on growth expectations are positive and signif-

A17 in the Appendix reports the results, showing that more optimistic macroeconomic expectations are associated with higher aggregate lending.

icant in all share, amount, and cost specifications, and they are stable across the three sets of fixed effects and controls. Loan maturity, by contrast, is unrelated to growth expectations in all three specifications. Based on the most saturated specifications in columns (3), (6), and (9), a one-standard-deviation increase in a bank's growth expectation for a country is associated with a 0.90 percentage point increase in its share of the loans extended to that country, which is 12.5% of the mean bank-country share, a 15.5% increase in the amount lent, and a 14.7 basis point increase in the amount-weighted average spread on its newly originated loans.[30] Given that the average amount a bank lends to a country in a month is $860 million, the amount effect corresponds to approximately $133 million of additional lending. The findings on loan shares and amounts confirm that the within-tranche reallocation documented in the baseline translates into aggregate differences in credit supply across banks.

Table 19: Bank-Country Aggregated Lending Terms

	Share			Ln(Amount)			Cost			Maturity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
L.GDP Growth Expectation	0.399**	0.523**	0.494**	0.061*	0.093**	0.085**	8.427**	9.730**	8.109**	1.289	0.634	0.276
	(0.196)	(0.252)	(0.245)	(0.035)	(0.043)	(0.042)	(3.513)	(3.816)	(3.897)	(0.794)	(1.057)	(1.052)
Observations	14281	14281	14281	14281	14281	14281	14281	14281	14281	14281	14281	14281
R^2	0.578	0.680	0.688	0.770	0.835	0.838	0.573	0.713	0.731	0.534	0.673	0.694
Bank Control	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lending Terms Control	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES
Borrower Country × Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank Country-Borrower Country Pair FE	NO	YES	YES	NO	YES	YES	NO	YES	YES	NO	YES	YES
Bank Country × Month FE	NO	YES	YES	NO	YES	YES	NO	YES	YES	NO	YES	YES

Notes: This table presents OLS estimates of equation 5, which regresses one of the four lending terms on the bank's GDP growth expectation for the country, lagged by one month. The data are aggregated at the bank-country-month level, and the dependent variable is indicated in the column titles. Specifically, *Share* denotes the bank's share of total loans extended to the country, *Ln(Amount)* is the natural logarithm of the total loan amount, *Cost* is the amount-weighted average borrowing cost measured in basis points above the risk-free rate, and *Maturity* is the amount-weighted average loan maturity in months. Lending terms controls are the contemporaneous lending terms other than the dependent variable. All specifications control for lagged bank characteristics and the bank's lagged outstanding loans to the country. Standard errors clustered at the bank-borrower-country level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

[30] Table A18 in the appendix reports summary statistics for the main variables in the bank-country-level dataset.

6 Further Discussions

6.1 State Dependence and Policy

We continue to explore whether banks that "storm in early" on optimism may lend more aggressively over the credit cycle. We distinguish a bank's current expectation from its disposition to optimism, measured as the share of previous months in which its forecast for the borrower country exceeded the consensus, centered at the sample mean. In addition, we identify the start of a syndicated-credit boom in the borrower country as the first month in which three-year growth in outstanding syndicated credit enters the top tercile after not having been in it a year earlier; boom starts account for about 3.5% of the observations.

Table 20 reports the triple interaction between the current expectation, optimism history, and the boom-start indicator. Outside boom starts, optimism history has no significant effect on loan shares, either directly or through the current expectation. At boom starts, lending becomes far more sensitive to current expectations: for a bank with an average optimism history, the coefficient on the growth expectation rises from 0.6 to about 5.5. The positive coefficient on optimism history interacted with the boom-start indicator and the negative triple interaction imply that this heightened sensitivity is weaker for habitually optimistic banks: one standard deviation more optimism history lowers the boom-start coefficient to about 1.4. Evaluated at the average expectation observed at boom starts, the level effect of optimism history is small and insignificant, so dispositionally optimistic banks do not take systematically larger shares when a boom begins. The evidence thus points to current expectations, not an entrenched optimistic tilt, as the margin on which banks position themselves at the onset of credit booms, with the response concentrated among banks whose optimism is not habitual and whose current forecast therefore carries more information.

We next examine whether the transmission of expectations to credit supply depends on the state of the borrower country's financial system and on its regulatory stance. Table

Table 20: Optimism History and Credit Boom

	(1)	(2)
L.GDP Growth Expectation	0.592***	0.572**
	(0.211)	(0.226)
Optimism History	2.626	2.663
	(3.193)	(3.415)
L.GDP Growth Expectation × Optimism History	-1.002	-1.111
	(0.855)	(0.910)
L.GDP Growth Expectation × D(Boom Start)	5.027**	4.896*
	(2.303)	(2.530)
Optimism History × D(Boom Start)	54.739***	55.155***
	(14.771)	(16.027)
L.GDP Growth Expectation × Optimism History × D(Boom Start)	-26.067***	-26.109***
	(8.375)	(9.062)
Observations	24308	24308
R^2	0.769	0.788
Bank Control	YES	YES
Borrower × Month FE	YES	-
Tranche FE	NO	YES
Bank Country × Month FE	YES	YES
Bank × Borrower Country FE	YES	YES

Notes: This table presents OLS estimates of the baseline specification augmented with interactions between the bank's GDP growth expectation, its optimism history, and an indicator for the start of a syndicated-credit boom in the borrower country. Optimism history is the share of previous months, with at least six months of history, in which the bank's forecast for the borrower country exceeded the consensus forecast, centered at the sample mean. A boom start is the first month in which three-year growth in total outstanding syndicated credit to the borrower country enters the top tercile after not having been in it twelve months earlier. The boom-start indicator varies at the borrower-country-month level and is absorbed by the fixed effects. The dependent variable is the loan share (in percentage points) funded by a bank in the tranche, and the key explanatory variable is the bank's GDP growth expectation for the borrower's country, lagged by one month. The inclusion of control variables and fixed effects is as specified. Standard errors clustered at the bank-borrower-country pair level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

21 interacts the bank's growth expectation with two sets of borrower-country conditions. Columns (1) and (2) use an indicator for a banking crisis in the borrower country-year, taken from the global crisis database of Reinhart and Rogoff (2009); crisis years account for about 23% of the observations for which the indicator is available. Columns (3) to (6) use the IMF integrated Macroprudential Policy (iMaPP) database of Alam, Alter, Eiseman, et al. (2025), which records monthly tightening and loosening actions across seventeen instruments. We measure the policy stance as the net number of actions in the borrower country over the twelve months preceding the loan, entered as a continuous variable in columns (3) and (4) and as an indicator for net tightening in columns (5) and (6). Net tightening precedes about one third of the loans in our sample.

During banking crises, the interaction is negative but imprecisely estimated, and the implied effect of expectations in crisis years is not significantly different from zero or from the non-crisis effect. The results for macroprudential policy depend on how the stance is

Table 21: Banking Crises, Macroprudential Policy, and the Effect of Growth Expectations

	Banking Crisis		Macroprudential Policies			
	(1)	(2)	(3)	(4)	(5)	(6)
L.GDP Growth Expectation	1.070***	1.057***	0.792***	0.775***	1.433***	1.419***
	(0.237)	(0.254)	(0.250)	(0.272)	(0.315)	(0.343)
L.GDP Growth Expectation × Banking Crisis	-2.199	-2.167				
	(1.601)	(1.747)				
L.GDP Growth Expectation × MacroPru Policies			-0.285	-0.284		
			(0.203)	(0.219)		
L.GDP Growth Expectation × D(Tight)					-4.321**	-4.340**
					(1.948)	(2.143)
Observations	19594	19594	25752	25752	25752	25752
R^2	0.767	0.783	0.769	0.788	0.769	0.788
Bank Control	YES	YES	YES	YES	YES	YES
Tranche Control	YES	-	YES	-	YES	-
Borrower × Month FE	YES	-	YES	-	YES	-
Tranche FE	NO	YES	NO	YES	NO	YES
Bank Country × Month FE	YES	YES	YES	YES	YES	YES
Bank × Borrower Country FE	YES	YES	YES	YES	YES	YES

Notes: This table presents OLS estimates of the baseline specification augmented with an interaction between the bank's GDP growth expectation and conditions in the borrower's country. Banking Crisis is an indicator for a banking crisis in the borrower country-year from the global crisis database of Reinhart and Rogoff (2009). MacroPru Policies is the net number of macroprudential tightening actions in the borrower country over the twelve months preceding the loan, and D(Tight) is an indicator for this number being positive, both from the IMF iMaPP database (Alam, Alter, Eiseman, et al., 2025). The direct effects of these variables are absorbed by the fixed effects. The dependent variable is the loan share (in percentage points) funded by a bank in the tranche, and the key explanatory variable is the bank's GDP growth expectation for the borrower's country, lagged by one month. Columns (1) and (2) are estimated on the subsample for which the crisis indicator is available. The inclusion of control variables and fixed effects is as specified. Standard errors clustered at the bank-borrower-country pair level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

measured. The interaction with the net number of actions is negative but small and insignificant, whereas the interaction with the tightening indicator is -4.3 and significant. Outside tightening episodes, the coefficient on expectations is 1.4, above the baseline estimate, while in the twelve months after net tightening the implied coefficient is about -2.9 and not significantly different from zero. The relation between banks' expectations and their loan shares is thus concentrated in periods without recent macroprudential tightening, and it is the occurrence of tightening rather than its intensity that matters. Since macroprudential actions respond to credit conditions, we read these estimates as descriptive. They are nonetheless consistent with the view that binding regulatory constraints limit the extent to which banks can act on their beliefs, and they complement the earlier finding that the effect of expectations is stronger when forecasters disagree, which also points to beliefs mattering most when lending is least constrained by common

information or common rules.

6.2 Inflation Expectation

Using the same regression specification, we substitute the GDP growth expectation with the inflation rate expectation for the current year to examine whether it also influences banks' lending decisions. Panel A of Table 22 presents the results. Interestingly, in contrast to growth expectations, banks' inflation expectations do not move their loan shares. The coefficient on the lagged inflation forecast is economically small and statistically indistinguishable from zero in every specification. This result is consistent with De Marco and Friedheim (2025), who show that inflation expectations do not affect credit supply for the average firm. In addition, we examine the roles of growth expectations and inflation expectations jointly. As shown in Panel B of Table 22, including both forecasts jointly leaves the growth-expectation effect unchanged and its magnitudes are comparable to those in the baseline results, while the inflation coefficient remains insignificant. Thus, the null is not an artifact of the moderate correlation between the two forecasts, and the growth channel is the operative one.

This muted effect of inflation expectation has a natural institutional explanation: syndicated lending is a floating-rate market. Virtually all tranches in our sample price over a short-term benchmark (only 0.17% are explicitly fixed-rate), so the bank's nominal return adjusts with policy and market rates as inflation materializes: expected inflation is hedged by contract design rather than borne by the bank. Beyond this, the sign of any residual exposure is theoretically ambiguous: higher expected inflation erodes nominal repayments but also lightens borrowers' real debt burdens and raises benchmark income, whereas expected growth maps unambiguously into borrower performance and default risk, which is where the allocation margin responds.

Consistent with the hedging interpretation operating across environments, the null is not overturned where inflation exposure should be most salient. As shown in Table A19 in the appendix, interacting the inflation forecast with high-inflation regimes, either

Table 22: GDP Growth and Inflation Expectation Together

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Inflation Expectation Alone									
L.Inflation Expectation	-0.262	0.302	0.306	0.365	0.351	0.022	0.034	-0.021	-0.003
	(0.766)	(0.676)	(0.674)	(0.827)	(0.893)	(0.663)	(0.672)	(0.724)	(0.732)
Observations	23642	23642	23642	23642	23642	23642	23642	23642	23642
R^2	0.710	0.729	0.730	0.740	0.759	0.765	0.765	0.784	0.784
Panel B: GDP Growth and Inflation Expectation Together									
L.GDP Growth Expectation	2.758***	2.328***	2.329***	2.716***	2.714***	0.703***	0.713***	0.692***	0.701***
	(0.649)	(0.586)	(0.585)	(0.512)	(0.566)	(0.240)	(0.240)	(0.259)	(0.259)
L.Inflation Expectation	-0.755	-0.120	-0.116	-0.119	-0.134	-0.106	-0.101	-0.147	-0.136
	(0.516)	(0.420)	(0.417)	(0.488)	(0.509)	(0.591)	(0.599)	(0.645)	(0.653)
Observations	23642	23642	23642	23642	23642	23642	23642	23642	23642
R^2	0.712	0.730	0.732	0.742	0.761	0.765	0.765	0.784	0.784
Bank Control	NO	YES	YES	YES	YES	YES	YES	YES	YES
Tranche Control	NO	NO	YES	YES	-	YES	YES	-	-
Borrower × Month FE	YES	YES	YES	YES	-	YES	YES	-	-
Tranche FE	NO	NO	NO	NO	YES	NO	NO	YES	YES
Bank Country × Month FE	NO	NO	NO	YES	YES	YES	YES	YES	YES
Bank FE	NO	NO	NO	NO	NO	YES	-	YES	-
Bank × Borrower Country FE	NO	NO	NO	NO	NO	NO	YES	NO	YES

Notes: This table presents the OLS estimates of the baseline specification, substituting the GDP growth expectation with the inflation expectation in Panel A and including both the bank's GDP growth expectation and its inflation expectation in Panel B. The dependent variable is the loan share (in percentage points) funded by a bank in the tranche. The key explanatory variables are the bank's expectations of the current-year GDP growth rate and inflation rate in the borrower's country, each lagged by one period. The inclusion of control variables and fixed effects is as specified. Standard errors clustered at the bank-borrower-country level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

defined as above 4 percent or the sample's 90th percentile, or with the borrower country's inflation-targeting status yields no significant interactions, though we note that high-inflation episodes are rare in our advanced-economy-dominated sample, so these regime tests are less powered than the baseline.

7 Conclusion

In summary, our study establishes that global banks' macroeconomic expectations regarding borrower countries shape their credit supply decisions. Exploiting granular within-firm variation in bank beliefs—by comparing multiple banks lending to the exact same firm concurrently—under saturated fixed effects, and supported by bounding exercises, randomization tests, and timing evidence, we document a robust link between optimistic

GDP growth forecasts and expanded credit provision. Quantitatively, a one-standard-deviation increase in a bank's GDP growth expectation for a destination country increases its loan share by 1.4 percentage points, and aggregates to 15% more lending to that market, or roughly $133 million per month for the average bank-country pair. These baseline results remain stable across a comprehensive battery of robustness checks.

Furthermore, we show that the transmission of beliefs to credit is strongest where a bank's own assessment adds most to the information shared by the syndicate: when forecasters disagree, for borrowers in less cyclical sectors, at the onset of credit booms, and among participant lenders rather than lead arrangers. It also depends on the bank's capacity to act: a bank's lending responds more to its expectations when its balance sheet is stronger than its own norm. The transmission is interrupted by macroprudential tightening and is otherwise invariant to lending relationships, cross-border status, and currency denomination. Unlike GDP growth forecasts, global banks' inflation expectations exert no statistically significant impact on credit supply, consistent with the floating-rate structure of syndicated lending.

These findings yield notable policy implications. First, by underscoring the first-order importance of global banks' expectations in driving credit, particularly at the onset of credit booms and when the outlook is contested, our results suggest macroprudential authorities should actively monitor the formation and dispersion of these beliefs. Second, the finding that recent macroprudential tightening severs the link between bank optimism and credit supply indicates that such tools are effective precisely in the states where belief-driven lending is most pronounced. Ultimately, transparent, reliable official forecasts are essential to anchor bank beliefs and stabilize lending.

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Global Banks' Macroeconomic Expectations and Credit Supply

Online Appendix

A1 DealScan Data Cleaning Process

We download all Refinitiv LoanConnector DealScan data from WRDS for period June 1981 to June 2024. The raw data has 2,907,345 obs. We clean the DealScan data based on the following procedures:

1. Deal with the problem of missing values of lender share (68.65% of the deals lack lender share information):
    - Divide the loan facility equally among all participants where exact lender shares are not available, and replace the lender share with missing if the value is negative and with 100 if the value is higher than 100
    - Use the filled loan shares to obtain the loan amount for each bank by multiplying the tranche loan amount
    - Note that we use only the sample with original lender shares in the main analysis, while the imputed loan shares and amounts are used as a robustness check
2. Keep closed or in process deals, drop the observations that are in the phases of canceled, rumor, on-hold, pre-mandate, or no further info (20,933 obs dropped)
3. Drop the amendment or extension of previous deals (31,120 dropped)
4. Exclude borrowing firms in the financial or utilities sector
5. Drop the 56 parent banks that are public development banks and export-import banks such as World Bank, European Investment Bank, Asian Development Bank, Export–Import Bank of China etc (26,050 obs dropped)
6. Drop if parent bank identifier is missing and some potential miscoding for borrowers in Indonesia (16,801 obs dropped)
7. Drop if tranche active date is earlier than October 1989 or later than December 2023 (125,714 obs dropped)
8. Aggregate affiliates of the same parent bank within each tranche by summing their lender shares, capped at 100%, so that each parent appears once per tranche

A2 FIRE Test

Here we summarize the model derivations from Coibion and Gorodnichenko (2015). According to the sticky-information model, denoting $1-\lambda$ as the probability of acquiring new information, thus λ measures the degree of information rigidity.

The current average forecast is a weighted average of the previous period's average forecast and the current rational expectation of variable x at time t+h:

$$F_t x_{t+h} = (1-\lambda)E_t X_{t+h} + \lambda F_{t-1} x_{t+h} \tag{6}$$

full-information rational expectations are such that:

$$E_t x_{t+h} = X_{t+h} - v_{t+h,t} \tag{7}$$

where $v_{t+h,t}$ is the full-information rational expectations error and uncorrelated with information dated t or earlier.

The relationship between the ex post mean forecast error across agents and the ex ante mean forecast revision is:

$$x_{t+h} - F_t x_{t+h} = \frac{\lambda}{1-\lambda}(F_t x_{t+h} - F_{t-1} x_{t+h}) + v_{t+h,t} \tag{8}$$

the coefficient on the forecast revision depends only on the degree of information rigidity λ.

According to the noisy-information model, agents continuously update their information sets but never fully observe the state.

Suppose a macro variable follows an AR(1) process:

$$x_t = \rho x_{t-1} + v_t \tag{9}$$

, agents cannot directly observe x_t but instead receive as signal y_{it} such that

$$y_{it} = x_t + \omega_{it} \tag{10}$$

Each agent then generate forecast given their information sets via the Kalman filter

$$F_{it} x_t = G y_{it} + (1-G) F_{it-1} x_t \tag{11}$$

$$F_{it} x_{t+h} = \rho^h F_{it} x_t \tag{12}$$

where G is the Kalman gain which represents the relative weight placed on new

information relative to previous forecasts. $1 - G$ can be interpreted as the degree of information rigidity in this model. The relationship between ex post mean forecast errors and ex ante mean forecast revisions is:

$$x_{t+h} - F_t x_{t+h} = \frac{1-G}{G}(F_t x_{t+h} - F_{t-1} x_{t+h}) + v_{t+h,t} \tag{13}$$

Based on both models, we can test the relationship between ex post mean forecast errors and ex ante mean forecast revisions using the following empirical specification:

$$x_{t+h} - F_t x_{t+h} = c + \beta(F_t x_{t+h} - F_{t-1} x_{t+h}) + error_t \tag{14}$$

$\beta > 0$ if information rigidities are present. With this regression, we can (1) extract an estimate of information friction based on $\hat{\beta}$; (2) predict a constant of zero (c); and (3) the coefficients on the contemporaneous and lagged forecast are equal in absolute value; (4) no other variables should have any additional predictive power for forecast errors conditional on forecast revisions.

A3 Additional Figures and Tables

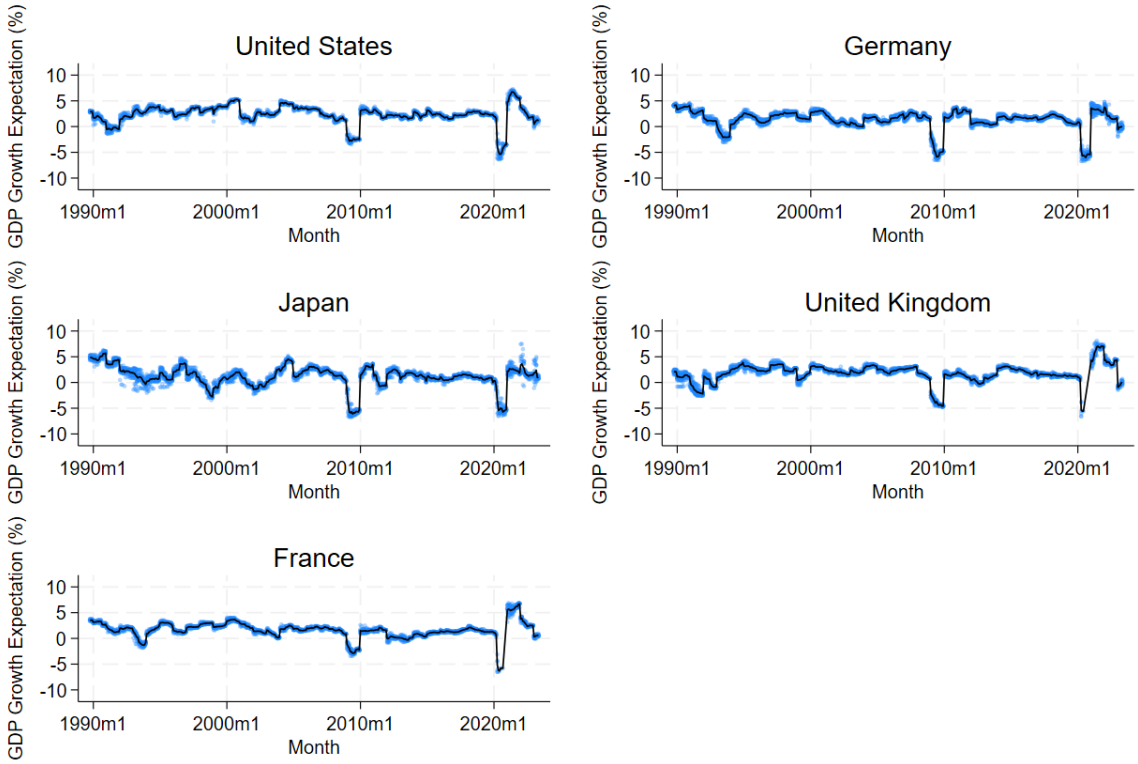


Figure A1: Scatter Plots of GDP Growth Expectation for G5 Countries

Notes: Each panel plots the current-year GDP growth forecasts reported to Consensus Economics by all banks in the database for the country indicated, one dot per bank and month, from January 1990 to the end of the sample. The solid line is the mean forecast across banks in each month.

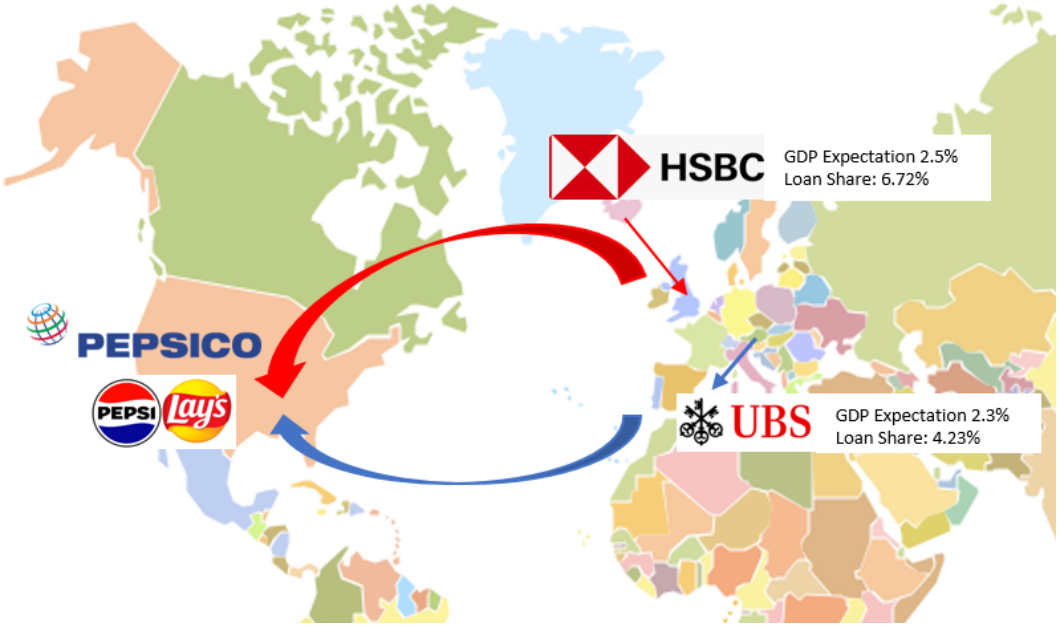


Figure A2: Illustration of the Loan Data

Notes: This figure uses an example to illustrate the data structure. In this example, a U.S. company, PepsiCo, obtained a syndicated loan from a group of global banks in June 2015, including HSBC and UBS, headquartered in the U.K. and Switzerland, respectively. The figure indicates that the two banks had different expectations for U.S. GDP growth in 2015 and different loan shares in this borrowing. About 60% of PepsiCo's sales are in the U.S. (33% in 2015), so U.S. growth bears directly on its loan performance. For most syndicated borrowers the headquarters' economy is the relevant one, and we subject our findings to many robustness tests with respect to the importance of the local and also U.S. economy.

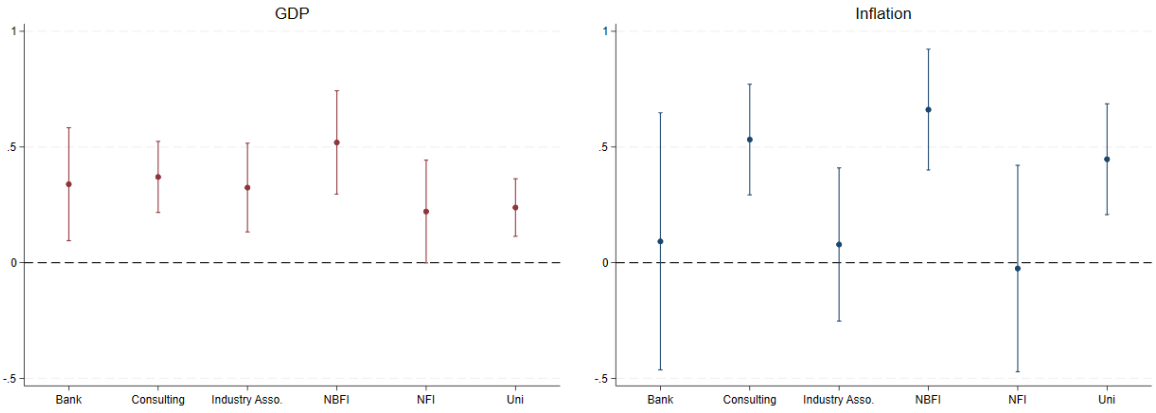


Figure A3: CG Test In Comparison with Other Types of Institutes

Notes: This figure presents the estimates of β from the CG test following Coibion and Gorodnichenko (2015) across different categories of forecasting institutes. 'Bank' denotes the global banks used in our main analysis; 'Consulting' includes consulting firms, rating agencies, and accounting agencies; 'Industry Asso.' refers to industry associations; 'NBFI' represents non-bank financial institutions; 'NFI' stands for non-financial firms; and 'Uni' denotes universities and public research institutes.

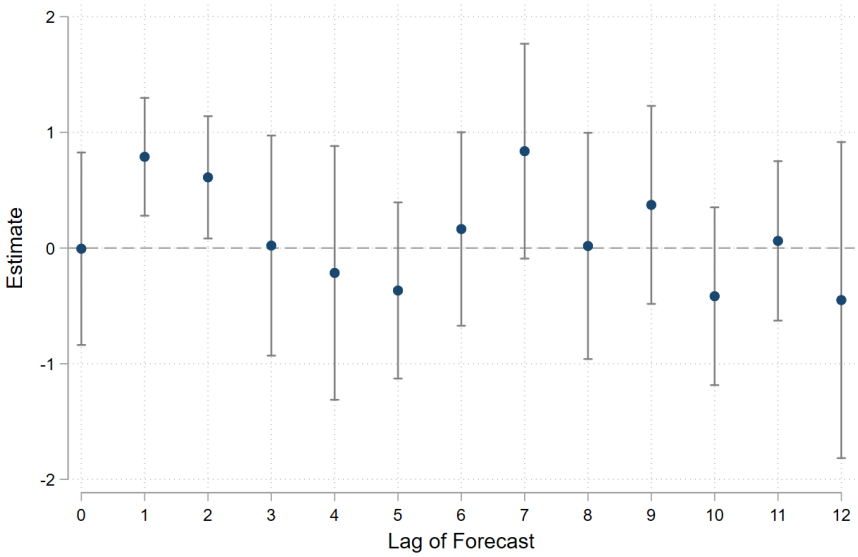


Figure A4: Coefficient Estimates Using Forecasts Lagged 0 to 12 Months

Notes: This figure presents the OLS estimates of β and their 95% confidence intervals from equation (4), where the one-month-lagged expectation measure is replaced, one at a time, by the corresponding measure lagged 0 to 12 months. All specifications include the baseline bank controls, the bank's outstanding loans to the borrower country, and tranche, bank-borrower-country pair, and bank-country-by-month fixed effects. Standard errors are clustered at the bank-borrower-country level.

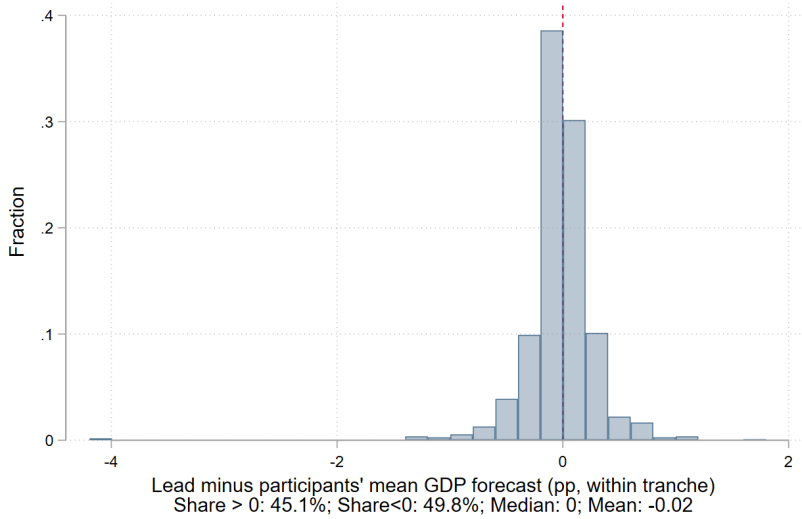


Figure A5: Lead Lenders' Versus Participants' Growth Expectations Within Tranches

Notes: This figure plots the distribution across tranches of the difference between the lead lenders' one-month-lagged GDP growth forecast for the borrower country and the mean forecast of the participant lenders in the same tranche, in percentage points. When a tranche has several lead lenders, their forecasts are averaged. The dashed line marks a gap of zero.

Table A1: Overview of Forecasting Institutes

Forecasting Institute Type	Number of Institute	of which forecast for at least two countries
Bank	195	121
Consulting and Rating Agencies	64	45
University and Research Institution	58	38
Non-bank Financial Institution	56	24
Non-financial Firms	28	17
Industry Association	27	19
	428	264

Table A2: Variable Definitions

Variable	Definition	Source
Loan Share (%)	The fraction (%) of loans funded by a bank in a syndicated loan tranche. The observation frequency can be at the exact date, but we use the month in which the loan was issued.	DealScan
GDP Growth Expectation (%)	The GDP growth rate forecast made by the bank for a given country in the current year. The observation frequency is monthly.	Consensus Economics
Ln(Asset)	The natural logarithm of the bank's total assets (in million USD). The observation frequency is annual.	BankFocus and authors' calculation.
Equity/Asset	The ratio (%) of total equity to total assets of a bank. The observation frequency is annual.	BankFocus and authors' calculation.
Depository Funding/Asset	The ratio (%) of depository funding to total assets of a bank. The observation frequency is annual.	BankFocus and authors' calculation.
Ln(Outstanding Loans)	The natural logarithm of the outstanding loan amount (in million USD) that the bank has lent to the borrower's country.	DealScan and authors' calculation.
Number of Banks	The number of banks participating in the syndicated loan tranche.	DealScan
Ln(Tranche Amount)	The natural logarithm of the total loan amount (in million USD) in the tranche.	DealScan
Tranche Maturity (months)	The maturity (in months) of the syndicated loan tranche.	DealScan

Table A3: List of Global Banks in Sample

Country	Bank Parent Name in DealScan	Forecaster in CE
Argentina	Argentaria Group	Argentaria
Belgium	Fortis Bank SA/NV [Dutch-Belgian Entity]	Fortis
Canada	BMO Capital Markets Financing Inc	BMO Capital Markets
	Desjardins Capital Markets	Desjardins
	National Bank of Canada	National Bank of Canada
	RBC Capital Markets	Royal Bank of Canada
	Scotiabank	Bank of Nova Scotia
	Toronto Dominion Bank	Toronto Dominion Bank
Denmark	Danske Bank A/S	Danske Bank
France	BNP Paribas SA	BNP Paribas
	BPCE SA	Natixis
	Credit Agricole Corporate & Investment Bank SA [Credit Agricole CIB]	Credit Agricole
	La Banque Postale SA	La Banque Postale
	Natixis SA	Natixis
	Societe Generale SA	Societe Generale
Germany	Commerzbank AG	Commerzbank
	DZ Bank AG	DZ Bank
	Deutsche Bank AG	Deutsche Bank
	Westdeutsche Genossenschafts-Zentralbank eG [WGZ-Bank]	WGZ Bank
Italy	Intesa Sanpaolo SpA [ISP]	Banca Intesa
	UniCredit	UniCredit
Japan	Mitsubishi UFJ Financial Group Inc	Bank of Tokyo-Mitsubishi UFJ
	Mizuho Financial Group Inc	Mizuho Financial Group
	Mizuho Leasing Co Ltd	Mizuho Financial Group
	Mizuho Leasing Co Ltd [ex-IBJ Leasing]	Mizuho Financial Group
	Nomura Holdings Inc	Nomura
	SBI Shinsei Bank Ltd [ex Shinsei Bank Ltd]	Shinsei Bank
	Sumitomo Mitsui Financial Group Inc	Sumitomo Bank
	Sumitomo Mitsui Trust Holdings Inc	Sumitomo Bank
Netherlands	ABN AMRO Bank NV	ABN AMRO
	ING Group	ING
	NIBC	NIB Capital
	Rabobank	Rabobank
Norway	DNB	DNB
	Nordea Bank AB	Nordea
Spain	Banco Bilbao Vizcaya Argentaria SA [BBVA]	BBVA
	Banco Santander SA	Grupo Santander
	Bankia [Banco Financiero y de Ahorros SA]	Bankia
	Caixabank SA	La Caixa
Sweden	SEB Merchant Banking AB	SEB
	Svenska Handelsbanken AB (publ) [SHBA]	Handelsbanken
	Swedbank AB (publ)	Swedbank
Switzerland	Credit Suisse AG	Credit Suisse
	UBS AG	UBS
	Zurcher Kantonalbank [ZKB]	Zürcher Kantonalbank
United Kingdom	Barclays	Barclays
	HSBC Banking Group	HSBC
	Lloyds Banking Group Plc	Lloyds
	Royal Bank of Scotland Plc [RBS]	RBS Financial Markets
United States	BofA Securities	Bank of America - Merrill
	Brown Brothers Harriman & Co	Brown Brothers
	CIBC	CIBC
	Citi	Citigroup
	Goldman Sachs & Co	Goldman Sachs
	JP Morgan	JP Morgan
	Morgan Stanley	Morgan Stanley
	Morgan Stanley MUFG Loan Partners LLC	Morgan Stanley
	Northern Trust Corp	Northern Trust
	PNC Bank	PNC Financial Services
	Prudential Financial Inc	Prudential Financial
	US Trust	United States Trust
	Wells Fargo & Co	Wells Fargo

Table A4: Summary Statistics of Cleaned DealScan Data

	Observed Loan Share					All Observations				
	Mean	SD	Min	Max	Count	Mean	SD	Min	Max	Count
Loan Share (%)	16.885	20.806	0.500	100.000	366297					
Number of Banks	12.341	11.414	1.000	362.000	366297	11.016	12.546	1.000	362.000	1296113
Ln(Tranche Amount)	4.939	1.699	-4.605	11.533	366161	4.865	1.663	-4.605	11.533	1294810
Tranche Maturity (Month)	56.540	40.229	0.000	732.000	359920	57.788	38.423	0.000	969.000	1245290

Notes: This table presents summary statistics of the key variables in the cleaned DealScan dataset, excluding the consideration of bank expectation data availability.

Table A5: CE Forecaster Banks: Matched Versus Unmatched to the Regression Sample

	(1) Not Matched	(2) Matched, Not in Regression	(3) In Regression	ND (2)-(1)	ND (3)-(2)
Number of Banks	83	57	55		
Countries Covered	1.24	1.60	5.82	0.313**	0.863**
Forecast-Months	102.11	140.82	694.95	0.256**	1.013**
Years in Panel	9.57	11.23	26.80	0.194	1.703**
Share of Forecasts on G5	0.53	0.68	0.41	0.329**	-0.670**
Mean Gap to Consensus (pp)	-0.00	-0.01	0.01	-0.054	0.247
Mean $\|Gap\|$ (pp)	0.22	0.21	0.19	-0.110	-0.274**
Share Above Consensus	0.48	0.50	0.51	0.063	0.129
Forecast S.D. (pp)	1.19	1.44	1.78	0.415**	0.610**
Share of Months Revised	0.50	0.52	0.55	0.116	0.133
Ln(Assets)	8.84	10.52	12.73	0.680**	1.104**
Equity/Assets (%)	14.07	9.36	5.90	-0.260**	-0.329**
Deposits/Assets (%)	68.53	68.94	64.20	0.022	-0.306**
ROAE (%)	6.91	9.30	9.95	0.194	0.083
HQ = US	0.21	0.21	0.16	0.013	-0.119

Notes: This table compares the 195 forecasting institutes that Consensus Economics classifies as banks and that report GDP growth forecasts, across three groups: banks not matched by name to any DealScan bank (column 1), banks matched to a DealScan bank but not in the regression sample for lack of balance sheet data or observed loan shares (column 2), and banks in the regression sample (column 3). Column (3) covers 55 of the 57 forecasting institutes in the regression sample, the remaining two being classified by Consensus Economics under other institute types. Forecast statistics are computed at the institute level over all country-months with a forecast; the gap to consensus is the institute's forecast minus the mean forecast across all CE forecasters for the same country-month, and the share above consensus and the share of months revised are the fractions of forecasts above that mean and of months in which the forecast changed. Balance sheet characteristics are institute-level averages from BankFocus over the years in which the institute is matched. The last two columns report normalized differences, $(\bar{x}_a - \bar{x}_b)/\sqrt{(s_a^2 + s_b^2)/2}$, between adjacent groups; ** marks absolute values above 0.25, the threshold suggested by Imbens and Wooldridge (2009).

Table A6: Loan Observations by Banks With and Without Forecast Data

	CE-Matched	Unmatched	Normalized Difference
Observations	856,538	551,360	
Borrower = US	0.46	0.35	0.215
Borrower in G5	0.70	0.56	0.290**
Cross-Border	0.55	0.28	0.567**
Bank = US	0.29	0.33	-0.076
Ln(Tranche Amount)	5.15	4.47	0.418**
Number of Banks	12.30	12.34	-0.003
D(Lead Arranger)	0.12	0.13	-0.032
Maturity (months)	56.28	60.19	-0.100
All-in Spread Drawn (bps)	191.04	218.54	-0.198
Mean Year	2007.14	2009.79	-0.333**
Share Post-2008	0.44	0.59	-0.292**

Notes: This table compares bank-tranche observations in the cleaned DealScan data originated between 1992 and 2022 by whether the bank is matched to a Consensus Economics forecaster. The last column reports the normalized difference, $(\bar{x}_1 - \bar{x}_0)/\sqrt{(s_1^2 + s_0^2)/2}$; ** marks absolute values above 0.25 (Imbens and Wooldridge, 2009).

Table A7: Observed Versus Imputed Loan Shares

	Fully-Known Tranche			Known and Imputed Shares			Exclude Fully-Imputed Tranches			Imputed Shares Only		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
L.GDP Growth Expectation	0.791***	0.830***	0.790***	0.342***	0.344***	0.350***	0.718***	0.723***	0.712***	-0.214	-0.197	-0.203
	(0.253)	(0.264)	(0.273)	(0.092)	(0.099)	(0.100)	(0.248)	(0.265)	(0.267)	(0.147)	(0.170)	(0.165)
Observations	22699	22699	22699	138948	138948	138948	26516	26516	26516	112225	112225	112225
R^2	0.769	0.784	0.785	0.888	0.904	0.905	0.759	0.777	0.778	0.945	0.956	0.956
Bank Control	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Tranche Control	YES	-	-	YES	-	-	YES	-	-	YES	-	-
Borrower × Month FE	YES	-	-	YES	-	-	YES	-	-	YES	-	-
Tranche FE	NO	YES	YES	NO	YES	YES	NO	YES	YES	NO	YES	YES
Bank Country × Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	-	YES	-	-	YES	-	-	YES	-	-	YES	-
Bank × Borrower Country FE	YES	NO	YES	YES	NO	YES	YES	NO	YES	YES	NO	YES

Notes: This table presents the OLS estimates of the baseline specification across samples that differ in how missing shares are treated. The dependent variable is the share of the tranche (in percentage points) funded by a bank. Columns (1) to (3) use only tranches in which the shares of all participating lenders are observed. Columns (4) to (6) use the full sample in which missing shares are imputed by allocating the unreported portion of the tranche equally across banks with missing shares. Columns (7) to (9) use the imputed sample but exclude tranches in which every bank's share is imputed. Columns (10) to (12) use only the imputed observations. The key explanatory variable is the bank's GDP growth expectation for the borrower's country, lagged by one month. All specifications include bank controls and the bank's outstanding loans to the borrower country; the inclusion of tranche controls and fixed effects is as specified. Standard errors clustered at the bank-borrower-country pair level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

Table A8: Loan Observations With and Without Reported Loan Shares

	Share Observed	Share Missing	Normalized Difference
Observations	400,216	989,572	
Borrower = US	0.36	0.44	-0.164
Borrower in G5	0.50	0.71	-0.446**
Cross-Border	0.46	0.43	0.062
Bank = US	0.24	0.33	-0.208
Ln(Tranche Amount)	4.98	4.85	0.075
Number of Banks	14.11	11.49	0.212
D(Lead Arranger)	0.15	0.11	0.111
Maturity (months)	56.42	58.28	-0.048
All-in Spread Drawn (bps)	149.88	227.00	-0.600**
Mean Year	2006.43	2008.87	-0.302**
Share Post-2008	0.44	0.52	-0.171

Notes: This table compares bank-tranche observations in the cleaned DealScan data originated between 1992 and 2022 by whether the bank's share of the tranche is reported. The last column reports the normalized difference, $(\bar{x}_1 - \bar{x}_0)/\sqrt{(s_1^2 + s_0^2)/2}$; ** marks absolute values above 0.25 (Imbens and Wooldridge, 2009).

Table A9: Baseline Estimation Sample Versus Observations Added by Imputation

	Baseline	Imputed Additions	Normalized Difference
Observations	25,752	112,580	
Borrower = US	0.43	0.34	0.187
Borrower in G5	0.73	0.78	-0.107
Cross-Border	0.15	0.20	-0.125
Bank = US	0.41	0.34	0.140
Ln(Tranche Amount)	5.38	5.11	0.159
Number of Parent Banks	12.27	8.99	0.397**
D(Lead Arranger)	0.14	0.12	0.061
Maturity (months)	52.81	55.66	-0.083
All-in Spread Drawn (bps)	157.43	232.90	-0.607**
Mean Year	2009.12	2011.98	-0.434**
Share Post-2008	0.61	0.72	-0.233

Notes: This table compares the bank-tranche observations in the baseline estimation sample with those added when missing loan shares are imputed, that is, observations in the imputed-share estimation sample whose share is not reported. The last column reports the normalized difference, $(\bar{x}_1 - \bar{x}_0)/\sqrt{(s_1^2 + s_0^2)/2}$; ** marks absolute values above 0.25 (Imbens and Wooldridge, 2009).

Table A10: Comparing Banks with and without Forecast Data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
D(Has Forecast)	6.840***	3.423***	3.423***	3.496***	3.411***	1.372***	-0.616	1.338***	-0.626
	(1.517)	(1.071)	(1.071)	(1.118)	(1.129)	(0.509)	(0.457)	(0.514)	(0.463)
Consensus Forecast × D(Has Forecast)	-0.417	-0.371	-0.371	-0.489**	-0.476*	-0.063	0.115	-0.054	0.123
	(0.273)	(0.235)	(0.235)	(0.245)	(0.247)	(0.132)	(0.139)	(0.132)	(0.141)
Observations	201399	201399	201399	201399	201399	201399	201399	201399	201399
R^2	0.667	0.698	0.698	0.709	0.726	0.743	0.754	0.759	0.769
Bank Control	NO	YES	YES	YES	YES	YES	YES	YES	YES
Tranche Control	NO	NO	YES	YES	-	YES	YES	-	-
Borrower × Month FE	YES	YES	YES	YES	-	YES	YES	-	-
Tranche FE	NO	NO	NO	NO	YES	NO	NO	YES	YES
Bank Country × Month FE	NO	NO	NO	YES	YES	YES	YES	YES	YES
Bank FE	NO	NO	NO	NO	-	YES	-	YES	-
Bank × Borrower Country FE	NO	NO	NO	NO	NO	NO	YES	NO	YES

Notes: This table presents the OLS estimates of loan shares regressed on a dummy variable indicating the bank's availability of forecast data and its interaction with the consensus GDP growth forecast. The inclusion of control variables and fixed effects is as specified. Standard errors clustered at the bank-borrower-country pair level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

Table A11: Subsample Periods Excluding COVID Crisis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L.GDP Growth Expectation	2.752***	2.353***	2.356***	2.790***	2.784***	0.683**	0.675**	0.668**	0.655**
	(0.690)	(0.644)	(0.642)	(0.556)	(0.615)	(0.265)	(0.269)	(0.288)	(0.292)
Observations	24671	24671	24671	24671	24671	24671	24671	24671	24671
R^2	0.714	0.732	0.733	0.743	0.761	0.766	0.766	0.784	0.785
Bank Control	NO	YES	YES	YES	YES	YES	YES	YES	YES
Tranche Control	NO	NO	YES	YES	-	YES	YES	-	-
Borrower × Month FE	YES	YES	YES	YES	-	YES	YES	-	-
Tranche FE	NO	NO	NO	NO	YES	NO	NO	YES	YES
Bank Country × Month FE	NO	NO	NO	YES	YES	YES	YES	YES	YES
Bank FE	NO	NO	NO	NO	-	YES	-	YES	-
Bank × Borrower Country FE	NO	NO	NO	NO	NO	NO	YES	NO	YES

Notes: This table presents the OLS estimates of the baseline specification using the sample of loans originated up to December 2019. The dependent variable is the loan share (in percentage points) funded by a bank in the tranche, and the key explanatory variable is the bank's GDP growth expectation for the borrower's country, lagged by one period. The inclusion of control variables and fixed effects is as specified. Standard errors clustered at the bank-borrower-country level are reported in parentheses.***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

Table A12: Horse Race with Expectation of Bank's Headquarter Country

	(1)	(2)
L.GDP Growth Expectation (Borrower Country)	1.214***	1.139***
	(0.356)	(0.368)
L.GDP Growth Expectation (Bank HQ Country)	-0.395	-0.334
	(0.336)	(0.344)
Observations	25050	25050
R^2	0.766	0.784
Bank Control	YES	YES
Tranche FE	NO	YES
Tranche Control	YES	-
Borrrower × Month FE	YES	YES
Bank Country × Month FE	YES	YES
Bank × Borrower Country FE	YES	YES

Notes: This table races the bank's GDP forecast for the borrower's country against its forecast for its own headquarters country, measured for the same bank and month with the same lag. Because the two forecasts coincide for domestic loans, the headquarters forecast cannot serve as a standalone placebo; the horse race lets the cross-border observations separate the two. Both columns are estimated on the common sample of tranche observations with headquarters-forecast coverage: column (1) uses the less saturated specification with borrower×month fixed effects and tranche controls, column (2) the saturated baseline specification with tranche fixed effects.

Table A13: Robustness Check: Excluding US-US Lending

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L.GDP Growth Expectation	2.831***	2.425***	2.424***	2.688***	2.688***	0.722**	0.752**	0.719**	0.747**
	(0.707)	(0.552)	(0.552)	(0.360)	(0.404)	(0.297)	(0.293)	(0.326)	(0.321)
Observations	15238	15238	15238	15238	15238	15238	15238	15238	15238
R^2	0.701	0.714	0.715	0.729	0.748	0.756	0.756	0.775	0.775
Bank Control	NO	YES	YES	YES	YES	YES	YES	YES	YES
Tranche Control	NO	NO	YES	YES	-	YES	YES	-	-
Borrower × Month FE	YES	YES	YES	YES	-	YES	YES	-	-
Tranche FE	NO	NO	NO	NO	YES	NO	NO	YES	YES
Bank Country × Month FE	NO	NO	NO	YES	YES	YES	YES	YES	YES
Bank FE	NO	NO	NO	NO	-	YES	-	YES	-
Bank × Borrower Country FE	NO	NO	NO	NO	NO	NO	YES	NO	YES

Notes: This table presents the OLS estimates of the baseline specification, excluding loans between US banks and US borrowers. The dependent variable is the loan share (in percentage points) funded by a bank in the tranche. The key explanatory variable is the bank's GDP growth expectation for the borrower's country, lagged by one period. The inclusion of control variables and fixed effects is as specified. Standard errors clustered at the bank-borrower-country level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

Table A14: Robustness Check: Controlling for Outstanding Loans at Firm-, Industry-, and Country-level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.GDP Growth Expectation	2.475***	2.474***	2.774***	2.774***	0.842***	0.760***	0.832***	0.748***
	(0.558)	(0.557)	(0.529)	(0.581)	(0.228)	(0.236)	(0.246)	(0.258)
L.Outstanding Loans to Borrower Country	0.008***	0.008***	0.005**	0.005**	0.001	-0.010***	0.001	-0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
L.Outstanding Loans to Borrower Industry	0.023	0.022	0.041*	0.039	0.030*	0.038**	0.028	0.036**
	(0.018)	(0.018)	(0.025)	(0.027)	(0.016)	(0.016)	(0.018)	(0.017)
L.Outstanding Loans to Borrower Firm	2.098***	2.096***	2.147***	2.124***	1.697***	1.675***	1.677***	1.655***
	(0.445)	(0.444)	(0.534)	(0.571)	(0.331)	(0.329)	(0.354)	(0.352)
Observations	25752	25752	25752	25752	25752	25752	25752	25752
R^2	0.729	0.730	0.742	0.761	0.769	0.769	0.788	0.788
Bank Control	YES	YES	YES	YES	YES	YES	YES	YES
Tranche Control	NO	YES	YES	-	YES	YES	-	-
Borrower × Month FE	YES	YES	YES	-	YES	YES	-	-
Tranche FE	NO	NO	NO	YES	NO	NO	YES	YES
Bank Country × Month FE	NO	NO	YES	YES	YES	YES	YES	YES
Bank FE	NO	NO	NO	-	YES	-	YES	-
Bank × Borrower Country FE	NO	NO	NO	NO	NO	YES	NO	YES

Notes: This table presents the OLS estimates of the baseline specification, replacing the bank's outstanding loans to the borrower country with the bank's outstanding loans to the borrower country, to the borrower's industry, and to the borrower firm, each measured as of the previous month and included jointly. The dependent variable is the loan share (in percentage points) funded by a bank in the tranche. The key explanatory variable is the bank's GDP growth expectation for the borrower's country, lagged by one period. The inclusion of control variables and fixed effects is as specified. Standard errors clustered at the bank-borrower-country level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

Table A15: Forecast Accuracy and Forecasting Experience

	GDP		Inflation	
	(1)	(2)	(3)	(4)
2-5y	-0.087*		-0.038	
	(0.050)		(0.031)	
5-10y	-0.066		-0.002	
	(0.045)		(0.030)	
>10y	-0.200***		-0.105***	
	(0.046)		(0.032)	
Experience Years		-0.021***		-0.022***
		(0.006)		(0.006)
Observations	10547	10547	9192	9192
R^2	0.752	0.755	0.539	0.545

Notes: This table presents OLS estimates relating the accuracy of banks' macroeconomic forecasts to their forecasting experience. The sample consists of the monthly current-year and next-year forecasts of GDP growth (columns 1 and 2) and inflation (columns 3 and 4) by the banks in the regression sample. The dependent variable is the absolute forecast error in percentage points, where the realized value is the first release in the April edition of the IMF World Economic Outlook. Experience is the number of years since the bank first reported a forecast for the country. Columns (1) and (3) include indicators for 2–5, 5–10, and more than 10 years of experience, with 0–2 years as the omitted category, and country-by-target-year fixed effects. Columns (2) and (4) use experience in years and add bank fixed effects. Standard errors clustered at the bank level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

Table A16: Do Lead Lenders Hold Different Expectations?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
D(Lead Lender)	-0.009	-0.007	-0.007	-0.006	-0.007	-0.004	-0.005	-0.005	-0.005
	(0.014)	(0.013)	(0.013)	(0.014)	(0.015)	(0.011)	(0.011)	(0.012)	(0.012)
Observations	25752	25752	25752	25752	25752	25752	25752	25752	25752
R^2	0.984	0.984	0.984	0.986	0.986	0.987	0.988	0.987	0.988
Bank Control	NO	YES	YES	YES	YES	YES	YES	YES	YES
Tranche Control	NO	NO	YES	YES	-	YES	YES	-	-
Borrower × Month FE	YES	YES	YES	YES	-	YES	YES	-	-
Tranche FE	NO	NO	NO	NO	YES	NO	NO	YES	YES
Bank Country × Month FE	NO	NO	NO	YES	YES	YES	YES	YES	YES
Bank FE	NO	NO	NO	NO	NO	YES	-	YES	-
Bank × Borrower Country FE	NO	NO	NO	NO	NO	NO	YES	NO	YES

Notes: This table regresses the bank's GDP growth expectation for the borrower's country, lagged by one month, on a dummy variable indicating whether the bank is a lead lender in the tranche, using the baseline estimation sample. The inclusion of control variables and fixed effects is as specified. Standard errors clustered at the bank-borrower-country pair level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

Table A17: Bank Macro Expectation and Aggregate Loan

	Loan-to-Asset Ratio				Ln(Loan)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.Domestic GDP Expectation	1.634***	1.083**	1.089**	0.787*	0.047	0.080**	0.077**	0.061**
	(0.522)	(0.510)	(0.511)	(0.439)	(0.036)	(0.033)	(0.032)	(0.027)
L.Bank Size		-10.785***	-11.010***	-7.466***		0.637***	0.741***	0.929***
		(1.199)	(1.337)	(1.030)		(0.065)	(0.076)	(0.064)
L.Equity-to-Asset Ratio			-0.048	-0.034			0.022***	0.025***
			(0.134)	(0.074)			(0.005)	(0.004)
L.Deposit-to-Asset Ratio				0.325***				0.017***
				(0.027)				(0.002)
L.Profitability				0.574				0.014
				(0.498)				(0.020)
Observations	1388	1388	1388	1388	1388	1388	1388	1388
R^2	0.699	0.746	0.746	0.790	0.930	0.946	0.947	0.959
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: This table presents OLS estimates from bank-year-level regressions. The dependent variable is either the loan-to-asset ratio or the logarithm of total loan amounts, as indicated in the column titles. The key explanatory variable is the bank's expectation of domestic GDP growth, lagged by one year. The inclusion of other control variables and fixed effects is as specified. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

Table A18: Summary Statistics of the Bank-Country Aggregated Sample

	Mean	Standard Deviation	Min	Max	N
Loan Share	7.181	7.392	0.000	98.804	14281
Ln(Loan Amount)	5.607	1.529	-4.786	10.125	14281
Loan Cost	100.285	119.691	0.000	1174.287	14281
Loan Maturity	51.343	28.359	0.000	721.000	14281
GDP Growth Expectation	1.772	1.818	-6.727	7.787	14281

Table A19: Inflation Expectation Across Regimes

	Inflation > 4%		Inflation > 90th Percentile		Inflation Targeting	
	(1)	(2)	(3)	(4)	(5)	(6)
L.Inflation Expectation	-0.032	-0.087	-0.009	-0.073	0.355	0.320
	(0.750)	(0.821)	(0.764)	(0.840)	(1.403)	(1.521)
L.Inflation Expectation × D(High Inflation)	0.470	0.592				
	(1.007)	(1.095)				
L.Inflation Expectation × D(High Inflation)			0.200	0.322		
			(0.857)	(0.932)		
L.Inflation Expectation × D(Inflation Targeting)					-0.884	-0.890
					(2.335)	(2.505)
Observations	23642	23642	23642	23642	23642	23642
R^2	0.765	0.784	0.765	0.784	0.765	0.784
Bank Control	YES	YES	YES	YES	YES	YES
Tranche Control	YES	-	YES	-	YES	-
Borrower × Month FE	YES	-	YES	-	YES	-
Tranche FE	NO	YES	NO	YES	NO	YES
Bank Country × Month FE	YES	YES	YES	YES	YES	YES
Bank × Borrower Country FE	YES	YES	YES	YES	YES	YES

Notes: This table presents the OLS estimates of the baseline specification with the inflation expectation as the key explanatory variable, augmented with an interaction term between the inflation expectation and an indicator for the borrower country's inflation regime. The regime is defined as realized inflation above 4% (columns 1 and 2), realized inflation above the sample's 90th percentile (columns 3 and 4), or an inflation-targeting framework being in place (columns 5 and 6). The direct effects of these indicators are absorbed by the fixed effects. The dependent variable is the loan share (in percentage points) funded by a bank in the tranche. The key explanatory variable is the bank's expectation of the current-year inflation rate in the borrower's country, lagged by one period. The inclusion of control variables and fixed effects is as specified. Standard errors clustered at the bank-borrower-country level are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.