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Global Banks' Macroeconomic Expectations and Credit Supply*

Abstract

We investigate how global banks' macroeconomic expectations for borrower countries influence their credit supply. Utilizing granular data on varying expectations among banks lending to the same firm at the same time, combined with an instrumental variable approach, we find that more optimistic GDP growth expectations for a borrower country are strongly linked to increased credit supply. Specifically, a one standard deviation increase in a lender's GDP growth expectation for the borrower's country corresponds to an increase of 8.46 percentage points in the loan share, equivalent to approximately 0.75 standard deviations of the loan share and $75.35 million in loan amount. In contrast, global banks' short-term inflation expectations do not show a significant impact on their credit supply.

Keywords: asymmetric information, credit supply, expectation, global banks

JEL classification: E32, F34

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1 Introduction

Expectations play a crucial role in shaping fundamental economic decisions that underpin macroeconomic dynamics (Coibion and Gorodnichenko, 2015; Gennaioli, Ma, and Shleifer, 2016). In international financial markets, aggregate-level evidence also underscores the importance of information as a key determinant of capital flows (Portes, Rey, and Oh, 2001; Tille and Wincoop, 2014). Financial intermediaries, particularly global banks, occupy a central position in facilitating these flows (Gabaix and Maggiori, 2015; Gabaix and Koijen, 2021). However, our understanding of the influence of global banks' macroeconomic expectations remains limited.

Do global banks' expectations regarding GDP growth and inflation significantly impact international bank lending? Relatedly, what characterizes their expectation formation process? Is it distinct from that of other institutions? Answering these questions is critical for advancing our understanding of banking flow dynamics and holds important implications for policymakers aiming to manage and regulate cross-border financial activities.

To empirically investigate this question, there are two major challenges. One is the data requirement: we need to observe lenders' macroeconomic expectations and their credit supply to foreign countries simultaneously. The other challenge is endogeneity, as macroeconomic expectations can be influenced by economic performance and lending activities. This study addresses these challenges as follows. First, we leverage a novel dataset that enables monthly observations of global banks' macroeconomic expectations for key economies. This dataset is integrated with syndicated loan data and balance sheet information of these banks. Second, by exploiting the granular structure of the data – where banks with differing expectations lend to the same firm at the same time – we focus on within-loan-tranche variations across lenders. By saturating the estimation with granular fixed effects, we control for credit demand effects and mitigate reverse causality, as loan performance is fixed while macroeconomic expectations vary across banks.

Additionally, we adopt an instrumental variable (IV) approach to enhance identification. Specifically, we use the initial expectations for a country's economic growth in a given year, as formulated at least one year prior, as an instrument for current expectations. This IV satisfies both the relevance condition and exclusion restriction, as it is predetermined and sufficiently distant from directly influencing current lending activities.

Our main findings are twofold. First, we conduct the full-information rational expectations test and show that global banks' GDP growth expectations exhibit information rigidities. Specifically, their probability of updating information, or the weight placed on new information, is approximately 0.74, comparable to that of other non-bank financial and non-financial institutions. Second, we find that macroeconomic expectations significantly influence global banks' lending decisions. In particular, a more optimistic outlook on a country's GDP growth rate is strongly associated with increased credit supply to borrowers in that country. Specifically, when a lender's growth expectation for a borrower country increases by one standard deviation, the bank's lending share to that country rises by 8.46 percentage points, which corresponds to approximately 0.75 standard deviations of the loan share. For an average syndicated loan tranche of $890.67 million, this corresponds to approximately $75.35 million. These main findings hold in tests following Oster (2019) concerning unobservable variables and remain robust across a battery of checks using alternative measures of loan shares, macroeconomic expectations, and subsamples across different periods and lender types.

In addition, we discuss the role of inflation expectations and find that, unlike GDP growth expectations, short-run inflation expectations for a borrower country show no significant association with banks' lending decisions. This insignificance can be attributed to the maturity structure of syndicated loans, which typically average over four years, rendering short-term inflationary fluctuations less relevant to lenders' decisions. Furthermore, we show that the influence of global banks' GDP growth expectations is particularly pronounced when loans are denominated in the borrower country's currency, during periods of positive news shocks, and for smaller banks and those with a lower dependence on stable funding sources. Lastly, beyond loan shares, the impact of macroeconomic expectations is also reflected in aggregated lending amounts, costs, and maturities.

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 empirical results, and provides related discussions. Finally, Section 6 concludes.

2 Related Literature

Our study contributes to three strands of literature. First, we relate to the literature on the information structure in expectations. Coibion and Gorodnichenko (2015) provide a framework for testing whether full-information rational expectations hold empirically. Their approach allows for the detection of rational expectations and information rigidities and explores how these vary with macroeconomic volatility. Bordalo, Gennaioli, Ma, et al. (2020) and Afrouzi, Kwon, Landier, et al. (2023) extend this discussion by employing diagnostic expectations within a dispersed information learning model and a model of expectations formation that incorporates the costly processing of past information to explain overreactions in macroeconomic expectations. Benhima, Blengini, and Merrouche (2022) demonstrate that local agents have an informational advantage over foreign agents, resulting in smaller forecasting errors of GDP growth and inflation. Regarding the determinants of inflation expectations, Malmendier and Nagel (2016) show that differences in inflation experiences strongly predict variations in expectations, while Dräger, Lamla, and Pfajfar (2024) find that information about rising inflation increases inflation expectations. In this context, our study examines the relationship between global banks' financial conditions and their macroeconomic expectations. We also highlight the value of actual expectations data in understanding economic behavior.

The second strand of literature focuses on the role of expectations in driving business cycles, a concept that dates back to Minsky (1977). Minsky argued that boom-bust patterns in credit and output growth reflect the expectations of economic agents. Specifically, overly optimistic investors and managers can lead to over-borrowing and over-investment, often preceding recessions. More recently, several studies have empirically documented the impact of firms' expectations on investment, production, and debt issuance, while also exploring the role of financial constraints (Gennaioli, Ma, and Shleifer, 2016; Ropele, Gorodnichenko, and Coibion, 2022; Gulen, Ion, Jens, et al., 2024; He, Su, and Yu, 2024). Cascaldi-Garcia (2024) explore the impact of news shocks. In our paper, we hold constant nonfinancial firms' performance, credit demand, and expectations to examine the role of lenders' expectations in shaping credit supply decisions.

Direct investigations of lenders' expectations have been scarce until recently, but this area is gaining increasing attention due to the critical role of financial intermediaries. Bassett, Chosak, Driscoll, et al. (2014) measure banks' responses to lending standards reported in the Federal Reserve's Senior Loan Officer Opinion Survey (SLOOS) on bank lending practices and construct a credit supply shock, demonstrating its substantial impact on lending capacity. Ma (2015) develop a measure of bank CEOs' optimism based on their bank stock holdings, showing its contribution to real estate loan expansions and crisis losses. Ma, Paligorova, and Peydro (2021) utilize expectations from a few U.S. banks on house prices and unemployment across metropolitan statistical areas to explore how lenders' expectations influence credit supply and real outcomes. Falato and Xiao (2023) use a model to explain banks' subdued lending following the global financial crisis, attributing it to over-pessimistic beliefs. D'Acunto, Gao, Liu, et al. (2025) conduct a survey experiment with loan officers from a large Chinese lending platform, eliciting their subjective expectations about macroeconomic variables and showing that these expectations are related to credit supply. Compared to these studies, our data are not limited to a single country; we cover cross-border bank lending and directly measure global banks' macroeconomic expectations for GDP growth and inflation in borrower countries. Our findings are consistent with the expectation-lending nexus observed in the literature.

Lastly, we contribute to the literature on macroeconomic expectations and capital flows. Malmendier and Nagel (2016) explore experience-based learning to understand international capital flows and portfolio investments. Cimadomo, Claeys, and Poplawski-Ribeiro (2016) and D'Agostino and Ehrmann (2014) examine the relationship between fiscal balance expectations and sovereign bond spreads. Stavrakeva and Tang (2024) reconnect macroeconomic fundamentals and exchange rates by analyzing macroeconomic news and expectations. Closer to our study, Benhima and Cordonier (2022) highlight the role of sentiment shocks and imperfect information in explaining the comovements of gross capital inflows and outflows. Benhima, Blengini, and Merrouche (2022) show that foreign currency borrowing in bond markets stems from disagreements between international and domestic borrowers. Additionally, Benhima, Bolliger, and Davenport (2023) use growth expectations to identify co-ownership spillovers and contagions in mutual fund flows, demonstrating how negative expectations about one country can adversely affect capital flows to other countries within the same fund's portfolio. Our study aligns with this literature by focusing on the role of macroeconomic expectations in driving capital flows. However, we concentrate specifically on global banks and their direct business operations in supplying credit.

3 Data and Variable

3.1 Macroeconomic Expectation

To measure lenders' macroeconomic expectations, we use data from Consensus Economics (CE). In the literature on expectations, various databases have been utilized to gauge 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 lenders' 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.[1] In each month, the forecaster provides the expectation of the GDP growth rate and inflation

[1] 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.

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 shows examples of GDP growth rate expectations for the U.S. and Germany over the period 2000M1-2022M12, as forecasted by three representative banks in our dataset: Bank of America (BoA), Wells Fargo, and Deutsche Bank. We observe that the U.S. GDP growth forecasts by BoA and Wells Fargo generally align with the consensus, which represents the average of all institutions in the CE database. However, notable deviations are evident: in some periods, BoA is more optimistic while Wells Fargo is more pessimistic relative to the consensus, and in other periods, both banks exhibit either greater optimism or pessimism. Similarly, it shows the GDP growth forecasts for Germany by BoA and Deutsche Bank, revealing clear variations between the two. For example, in 2021, Deutsche Bank's forecasts are consistently above the consensus, whereas BoA's forecasts fall below it. This disagreement among banks regarding macroeconomic growth expectations provides a solid foundation for examining the role of these expectations in their lending decisions.

Figure 1 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 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. Later in the analysis, we will use the initial expectation as an instrumental variable for the current expectation. This figure underscores the relationship between the initial and current expectations while highlighting the potential for substantial differences, supporting the validity of our identification strategy.

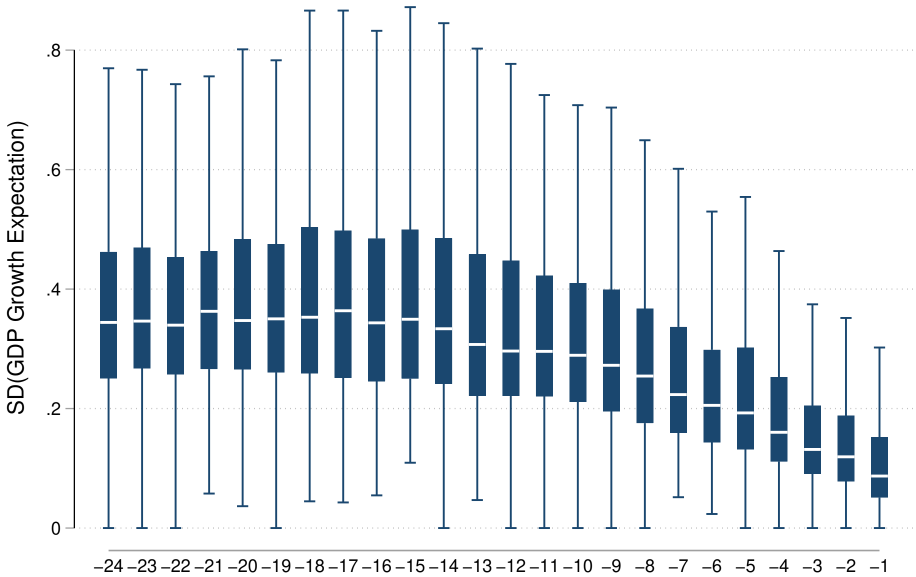


Figure 1: SD of GDP Growth Expectation Over the 24 Months Horizon

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 171,438 deals and 263,281 tranches originated between October 1989 and January 2024, involving 10,638 lenders and 71,791 borrowers.

For each loan, we know a rich set of information on the origination such as the the date and the identity of the borrower and the lender, and the details of loan terms including the toal amount, interest rate, and maturity. The variations across banks within a loan tranche are shown in their lender shares, which measures the credit supply by each lender and is the key explained variable in our study. A big issue with the DealScan database is the large fraction (about 60%-70%) of missing values of the lender share variable. 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 results in large measurement errors. Therefore, we stick with the small sample of un-imputed lender shares in the main analysis, and report in the robustness check that our main findings still hold with the larger but imputed sample.

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 example 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.[2] Note that the 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.[3] Of the 195 banks in CE, 142 are matched to parent lenders in DealScan, and 139 are matched to banks in the BankFocus databases.

As a result, the final dataset for the baseline analysis with un-imputed lender shares

[2]Thus, our final sample consists only of banks with forecast data. To explore the differences between banks with and without forecast data, we run a regression of the loan share on a dummy variable indicating forecast data availability, as well as its interaction with the consensus forecast. The results, presented in Appendix Table A4, indicate that banks with forecast data tend to have a higher loan share. Moreover, the effect of a higher growth consensus on loan share is smaller for these banks compared to those without forecast data, suggesting that they rely more heavily on their own forecasts.

[3]This process is assisted with the fuzzy match command in Stata, however, every lender/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.

comprises 9,145 deals and 12,230 tranches originated between January 1993 and December 2022. These transactions involve 70 global banks headquartered in 16 countries and 5,209 borrowers headquartered in 17 countries.[4] Table 1 presents summary statistics of the key variables used in this study, with their definitions provided in Table A2 in the appendix.[5]

Table 1: Summary Statistics

	Mean	Standard Deviation	Min	Max	N
Lender Share (%)	14.670	13.150	0.460	100.000	37725
GDP Growth Expectation (%)	2.096	1.706	-6.700	7.400	37725
Ln(Asset)	14.038	2.838	7.428	21.543	37725
Equity/Asset	5.587	3.415	-2.145	111.449	37725
Depository Funding/Asset	63.696	23.672	0.291	187.897	37725
Ln(Outstanding Loans)	11.109	1.570	1.847	13.446	37725
Number of Lenders	12.218	9.046	1	156	37725
Ln(Tranche Amount)	5.339	1.756	-2.040	10.800	37725
Tranche Maturity (months)	50.862	33.630	1	462	37725

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.

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. 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 lenders 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

[4]The 16 lender countries are: Argentina, Belgium, Canada, Denmark, France, Germany, Italy, Japan, Netherlands, Norway, South Africa, Spain, Sweden, Switzerland, United Kingdom, and United States. The 17 borrower countries are Belgium, Canada, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, Nigeria, Norway, South Africa, Spain, Sweden, Switzerland, United Kingdom, and United States.

[5]Table A3 in the appendix presents the characteristics of the tranches in the cleaned DealScan dataset, excluding consideration of the availability of lender expectation data. We observe that the loan shares and the number of lenders 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.

of our dataset, which enables us to analyze the credit supply decisions of lenders 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 first examine how global banks form their macroeconomic expectations by performing a full-information rational expectations (FIRE) test, following Coibion and Gorodnichenko (2015).

Specifically, Coibion and Gorodnichenko (2015) derive 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 mean forecast errors and ex ante mean forecast revisions are the following:

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

where $F_t x_{t+h}$ 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, $x_{t+h} - F_t x_{t+h}$ represents the forecast error, and $F_t x_{t+h} - F_{t-1} x_{t+h}$ captures the forecast revision between t and $t - 1$.

If the 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.[6] Importantly, evidence of information rigidities arises if we find $\beta > 0$. We apply this FIRE 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 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.

Table 2: FIRE Test

	GDP		Inflation	
DepVar: Forecast Error	(1)	(2)	(3)	(4)
Forecast Revision	0.319**	0.344***	0.099	0.106
	(0.129)	(0.127)	(0.282)	(0.286)
Constant	-0.329***	-0.712***	0.076***	0.029
	(0.033)	(0.242)	(0.022)	(0.170)
Observations	2315	2315	2070	2070
R^2	0.004	0.042	0.001	0.006
Horizon FE	NO	YES	NO	YES

Notes: This table presents the results of the FIRE test using the mean forecast revisions and forecast errors for each country-year. Forecast revision is defined as the difference between the forecast in the current month and the previous month. Forecast error is the difference between the realized value of the macroeconomic variable and the forecast. The horizon is the interval between the month the forecast is made and the year-end month of the realization of the macroeconomic variable. Horizon fixed effects are specified as indicated.

Table 2 presents the results. We find evidence of information rigidities in the formation of GDP growth expectations. Columns (1) and (2) show that forecast revisions are significantly and positively associated with 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,

[6] 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.

the relationship between forecast revisions and forecast errors is statistically insignificant, indicating no clear evidence against the FIRE hypothesis.

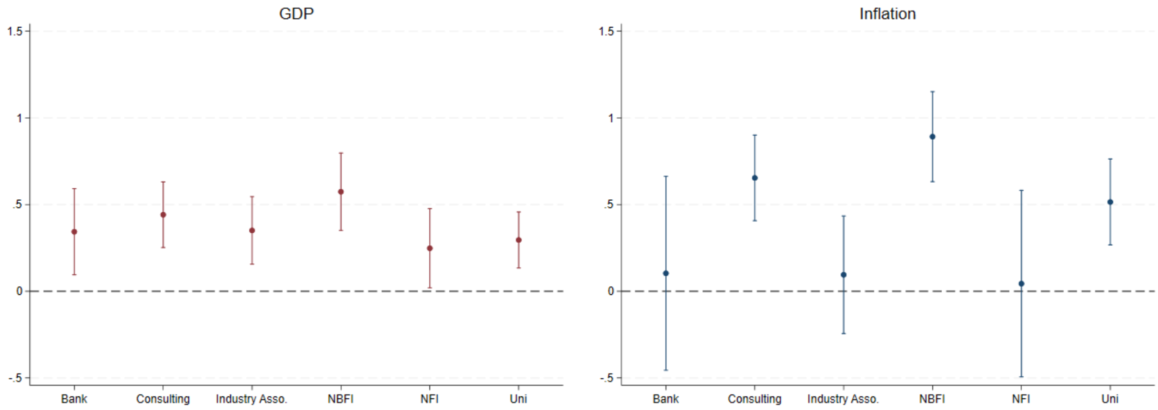


Figure 2: FIRE Test In Comparison with Other Types of Institutes

Notes: This figure presents the estimates of β from the FIRE test 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.

Our findings on growth expectations and the magnitude of information rigidities are consistent with those documented in Coibion and Gorodnichenko (2015). However, 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 FIRE test to forecasts from other types of institutions included in the Consensus Economics dataset. Figure 2 plots the estimated β coefficients from the FIRE 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.

To sum up, we find that the formation of GDP growth expectations among our sampled banks exhibits information rigidities. In contrast, we do not find evidence that their inflation expectation formation deviates from the FIRE assumption.

5 Macroeconomic Expectation and Credit Supply

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

5.1 Identification Strategy

In the baseline analysis, we first adopt the following specification:

$$LenderShare_{b,i,l,t} = \alpha_0 + \beta Expect_{b,i',t-1} + \alpha_1 Bank_{b,t-1} + \alpha_2 Loan_{b,i',t-1} + \theta_l + \lambda_{b',t} + \eta_{b',i'} + \epsilon_{i,b,l,t} \tag{2}$$

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 is located (hereafter borrower-country and lender-country), respectively. The dependent variable $LenderShare_{b,i,l,t}$ is the share of 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 $t-1$. We are mostly interested in the estimates of β. A statistically significant estimate of β demonstrates that banks' macroeconomic expectations are associated with the loan allocation across banks. Specifically, a positive β indicates that a lender's more optimistic expectations of the borrower country's economic growth are associated with larger share of loans financed by the lender, in relative to other lenders.

For control variables, we include a set of bank-level characteristics in $Bank_{b,t}$, including 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 asset. Since the bank-level variables are only available at bank-year level from the BankFocus database, we lag these variables by one year. $Loan_{b,i',t-1}$ represents the logarithm of the outstanding loans of the bank in the borrower country as of the previous month, which captures the lending history and the debt overhang between the lender and the borrower country.

With the level of granularity in our data, we can enrich the model by incorporating various fixed effects. θ_l indicates the fixed effects at the loan tranche level. As described in Section 3.2, within the loan tranche l, there are several banks financing the borrower at the same time, and the number of lenders, total loan amount, borrowing cost, and maturity are the same in one tranche, while loan shares differ across banks within a tranche. By fixing the loan tranche, θ_l also accounts for any confounding factors specific to a given borrower in a particular month and controls for credit demand, in the spirit of Khwaja and Mian (2008). Therefore, the estimates of β arise from the variations at the lender-level and captures the credit supply effect. In addition, it saturates the actual economic fundamentals and any policy changes of the borrower country at the given time point. In the estimation, before specifying the tranche fixed effect, we also show the results of including the borrower-month fixed effect $\theta_{i,t}$ and controlling for the tranche-level loan terms including the number of lenders, total loan amount, and maturity.[7] $\lambda_{b',t}$ is the bank country-month fixed effect that captures the economic development in the lender's home country. Thus, we examine the role of expectation of the borrower country given the lender country's macroeconomic conditions. Finally, $\eta_{b',i'}$ controls for factors that vary within the lender country-borrower country pair but do not vary with time, for instance, the long-built lending relationship and the cultural or legacy proximity between the country pair. We estimate the regressions using heteroskedasticity-robust standard errors to account for potential heteroskedasticity in the residuals.

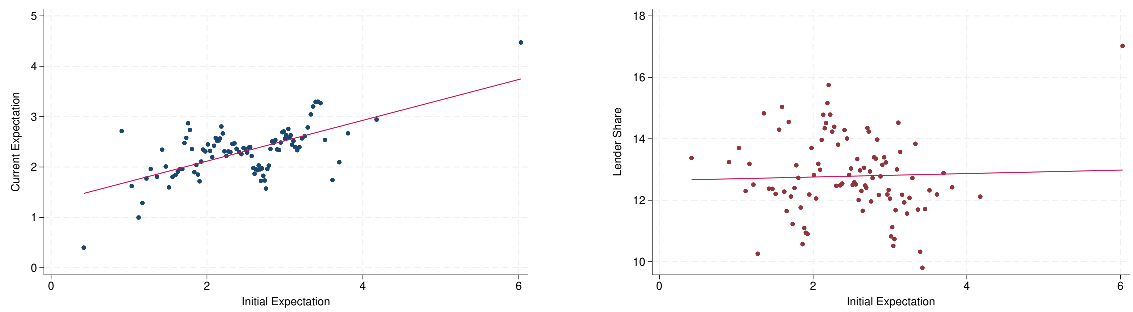
A causal identification of β in Equation (2) relies on the assumption that, conditional on the control variables, the lender's expectations about a country's macroeconomic per-

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

formance 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. For instance, if a lender's higher loan exposure to a country makes it more optimistic (or pessimistic) about the country's economic growth, this would lead to an overestimation (or underestimation) of β. To address this concern, we use the lagged value of the lender's expectation and controlled for the outstanding loan exposures to the borrower country in the regression. Additionally, since our dependent variable is at the bank-firm level, it is reasonable to assume that a bank's micro-level lending decisions would not significantly influence macroeconomic expectations about the borrower country. Second, there may be omitted variables that simultaneously affect a lender's expectations of a country and its credit supply to firms in that country. Importantly, such omitted variables must vary at the bank-borrower country or bank-firm level, which can be largely controlled for through the loan characteristics and the outstanding loans between a bank and a country. Moreover, any country-level variation is absorbed by the granular fixed effects included in the regression. These strategies significantly mitigate, though cannot entirely eliminate, concerns about endogeneity.

We enhance the identification strategy by employing an instrumental variable (IV) approach. Specifically, we leverage a feature of the CE expectation dataset, where each institute produces 24 forecasts for a country's GDP growth rate in a given year. These forecasts are updated monthly, spanning from January of the previous year to December of the current year. Our IV is the first forecast made for a given country-year, which we use to instrument the key explanatory variable – the forecast made in the current month. For example, we instrument Credit Suisse's expectation in August 2016 for U.S. GDP growth in 2016 using its forecast made twenty months earlier, in January 2015.

This choice of IV is validated as follows. First, it satisfies the relevance condition, as the forecast made in January 2015 for the U.S. growth rate in 2016 is significantly correlated with the forecast made in August 2016. This is because both forecasts are likely based on the same forecasting model and the same set of fundamental economic variables reflecting developments in 2016. Second, it satisfies the exclusion restriction, meaning that the initial forecast made in January 2015 should not influence Credit Suisse's loans to a U.S. firm in August 2016, except through its impact on expectations in August 2016. It is challenging to argue that an expectation formed twenty months earlier could directly affect lending decisions in the current month. In other words, in our setting, the initial forecast is predetermined when viewed from the perspective of the current month and is not directly connected to the economic conditions that have evolved in recent months. At any given point, the time gap between the initial forecast and the current forecast ranges from twelve to twenty-four months, which we believe is sufficiently long to rule out a direct impact of the initial forecast on current lending decisions.



(a) Initial and Current Expectation **(b)** Initial Expectation and Lender Share

Figure 3: Visualization of the First Stage

Notes: This figure shows the binned scatterplot of the relationship between the IV (the banks' initial GDP growth forecast) and the instrumented variable (the banks' current GDP growth forecast) on the left, and the relationship between the IV and the dependent variable (the banks' loan share) on the right. The plot uses 100 equally-sized bins along the horizontal axis, based on the IV. The solid lines represent fitted lines from auxiliary regressions, which include the same set of control variables as in the baseline analysis.

Figure 3 visualizes the first-stage relationship using bin scatter plots. These plots illustrate the relationships between the initial GDP growth expectation and the current expectation, as well as between the initial expectation and the lender share. Specifically, the initial GDP growth expectation is divided into 100 equally sized bins along the horizontal axis, with the mean values of the current expectation and lender share plotted on the vertical axis. The results reveal a positive correlation between the instrumental variable and the key explanatory variable, with a coefficient of 0.41 that is statistically significant at the 1% level. In contrast, no clear correlation is observed between the instrumental variable and loan share, as indicated by a coefficient of 0.06 that is not statistically significant.

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 recommendations 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

Now we turn to the baseline results. Table 3 presents the OLS estimates, incorporating control variables and various fixed effect specifications step by step. The coefficient of the key variable of interest – the banks' expectation of the GDP growth rate in the borrower country – ranges from 1.8 to 2.2 and remains statistically significant at the 1% level across all specifications. These results indicate that a lender's more optimistic macroeconomic expectations are significantly associated with an increase in credit supply. The estimated impact is also economically meaningful. Specifically, in column (8), where the model includes the full set of control variables and the most saturated fixed effects, a one standard deviation increase in a bank's GDP growth expectation for a country is associated with a 3.64 percentage point increase in its share of loans to borrowers in that country. This corresponds to 0.3 standard deviations of the loan share. Given that the average loan tranche in our sample is approximately 748 million dollars, this increase in loan share translates to about 27.22 million dollars.

For the other control variables, we find that bank size, leverage, and depository funding ratios are negatively associated with a lender's share in a tranche. In addition, a higher volume of existing outstanding loans between a bank and a borrower country is significantly associated with a higher loan share, highlighting the importance of lending relationships. Within a tranche, an average bank's loan share tends to decrease when the tranche involves more lenders or a larger financing amount, while tranche maturity does not exhibit a significant effect.

Table 3: OLS Estimates: GDP Growth Expectation and Lender Share

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.GDP Growth Expectation	2.107***	1.840***	1.835***	1.885***	2.193***	1.768***	1.817***	2.131***
	(0.247)	(0.248)	(0.247)	(0.252)	(0.278)	(0.254)	(0.259)	(0.288)
L.Ln(Asset)		-0.097*	-0.094*	-0.061	-0.127**	-0.092*	-0.092	-0.159**
		(0.055)	(0.054)	(0.056)	(0.063)	(0.052)	(0.057)	(0.065)
L.Equity/Asset		-0.023*	-0.023*	-0.036***	-0.038**	-0.023**	-0.032**	-0.033**
		(0.012)	(0.012)	(0.013)	(0.016)	(0.012)	(0.013)	(0.016)
L.Depository Funding/Asset		-0.020***	-0.020***	-0.021***	-0.027***	-0.020***	-0.021***	-0.027***
		(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
L.Ln(Outstanding Loans)		1.465***	1.449***	1.450***	1.506***	1.461***	1.469***	1.528***
		(0.047)	(0.046)	(0.056)	(0.061)	(0.048)	(0.059)	(0.064)
Number of Lenders			-0.291***	-0.291***	-0.286***			
			(0.045)	(0.045)	(0.046)			
Ln(Tranche Amount)			-0.326***	-0.328***	-0.316***			
			(0.099)	(0.098)	(0.098)			
Tranche Maturity			-0.004	-0.004	-0.004			
			(0.004)	(0.004)	(0.004)			
Observations	37725	37725	37725	37725	37725	37725	37725	37725
R^2	0.709	0.715	0.716	0.717	0.723	0.730	0.731	0.737
Bank Control	NO	YES	YES	YES	YES	YES	YES	YES
Tranche Control	NO	NO	YES	YES	YES	-	-	-
Borrower × Month FE	YES	YES	YES	YES	YES	-	-	-
Lender Country-Borrower Country Pair FE	NO	NO	NO	YES	YES	NO	YES	YES
Tranche FE	NO	NO	NO	NO	NO	YES	YES	YES
Lender Country × Month FE	NO	NO	NO	NO	YES	NO	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. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

From Table 3, the coefficients of the key explanatory variable, lagged GDP growth expectation, are stable across specifications using different sets of control variables and fixed effects. To further mitigate concerns about omitting variables and unobservable selections, we follow the methods in Oster (2019) and calculate the bounding sets and the degree of selection on unobservables relative to observables that would be necessary to explain away the results. Results are shown in Table 4, where we present the results using different assumptions of R_{max}, the R-squared from a hypothetical regression including unobservable controls. $\tilde{R}$ is the R-squared by including all observable controls, as shown in column (8) of Table 3. δ is the proportionality of the selection between unobservables and observables, and $\tilde{\delta}$ is the calculated degree of selection to generate an estimate of $\beta = 0$ for given R_{max}.[8] We see that all bounding sets exclude zero and are positive, and our estimated coefficient in the baseline (2.131) is the lower bound. Moreover, the unobservables would need to be at least twice as important as the observables and work in the opposite direction in correlation with our key explanatory variable, to produce a treatment effect of zero of the banks' macroeconomic expectation. These findings imply an unlikely bias of our estimates by unobservables.

Table 4: Bounding Estimates

R_{max}	Bounding Set	$\tilde{\delta}$ for $\beta = 0$ given R_{max}
$R_{max} = 0.85$ $(1.15\tilde{R})$	[2.131,2.594]	-4.561
$R_{max} = 0.92$ $(1.25\tilde{R})$	[2.131,2.881]	-2.828
$R_{max} = 0.96$ $(1.3\tilde{R})$	[2.131,3.044]	-2.324
$R_{max} = 1$	[2.131,3.208]	-1.972

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}.

As described in Section 5.1, we enhance the identification by using the first GDP growth rate forecast made at least one year prior as an instrumental variable for the current forecast.[9] Table 5 presents the results obtained from the IV approach and the two-stage least squares (2SLS) regression analysis. The first-stage results show that our instrumental variable, the bank's initial forecast of the GDP growth rate, is significantly

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

[9]Since we require a gap of at least 12 months between the instrument and the current forecast in the IV estimation, the number of observations is smaller than in the OLS estimation. Table A5 in the appendix reports the summary statistics for the IV estimation sample, which differ only slightly from those presented in Table 1.

correlated with the bank's current forecast. Furthermore, it consistently produces high values for the first-stage effective F-test, calculated using the method outlined in Olea and Pflueger (2013). This indicates that our estimates are not subject to the bias associated with weak instruments, as discussed by Stock and Yogo (2005). From the second-stage results, we find that all coefficient estimates for GDP growth expectations are statistically significant and positive, with magnitudes ranging from 2.7 to 5.4. This suggests that the OLS regression underestimates these effects. At the same time, the IV approach increases the OLS estimates by at most 2.5 times – well below the ratios reported in Jiang (2017), which indicate "implausibly large" IV estimates. Based on the estimate shown in column (8), if the bank's GDP growth expectation of the borrower country is larger by one standard deviation, its lending share to the borrower in that country tend to increase by 8.46 percentage points, which corresponds to approximately 0.75 standard deviations of the lender share. For an average tranche size of $890.67 million in the IV estimation sample, this corresponds to approximately $75.35 million.

Table 5: 2SLS Estimates: GDP Growth Expectation and Lender Share

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Second-Stage Results				
L.GDP Growth Expectation	3.752***	2.737**	2.765**	3.747***	5.167***	2.912***	3.846***	5.422***
	(1.177)	(1.085)	(1.079)	(1.252)	(1.561)	(1.111)	(1.284)	(1.614)
Observations	27680	27680	27680	27680	27680	27680	27680	27680
F-Stat	10.158	165.077	105.477	81.816	78.467	150.991	115.504	110.600
Bank Control	NO	YES	YES	YES	YES	YES	YES	YES
Tranche Control	NO	NO	YES	YES	YES	-	-	-
Borrower × Month FE	YES	YES	YES	YES	YES	-	-	-
Lender Country-Borrower Country Pair FE	NO	NO	NO	YES	YES	NO	YES	YES
Tranche FE	NO	NO	NO	NO	NO	YES	YES	YES
Lender Country × Month FE	NO	NO	NO	NO	YES	NO	NO	YES
				First-Stage Results				
Initial GDP Growth Expectation	0.091***	0.096***	0.096***	0.089***	0.086***	0.096***	0.088***	0.085***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Effective F-Stat	416.006	447.259	447.331	371.876	287.657	396.344	329.255	254.831

Notes: This table presents the two-stage least squares (2SLS) estimates of the baseline specification. The upper panel shows the second-stage results, where the dependent variable is the loan share (in percentage points) funded by a bank in the tranche, and the key explanatory variable is the instrumented bank's GDP growth expectation for the borrower's country, lagged by one period. The lower panel displays the first-stage results, where the dependent variable is the GDP growth expectation, and the key explanatory variable is the instrumental variable, i.e., the initial GDP growth expectation. The inclusion of control variables and fixed effects is as specified. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

5.3 Robustness Checks

We conduct a series of robustness checks on our baseline results. First, we show that the main findings remain robust when using the imputed lender shares, which are obtained by equally allocating the missing shares. Table 6 presents the 2SLS estimates.[10]

Table 6: Robustness Check: Using Imputed Lender Shares

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Second-Stage Results				
L.GDP Growth Expectation	0.817**	0.693**	0.693**	0.935***	1.190***	0.687**	0.889***	1.127***
	(0.343)	(0.333)	(0.314)	(0.353)	(0.398)	(0.270)	(0.304)	(0.349)
Observations	146361	146361	146361	146361	146361	146361	146361	146361
F-Statistics	5.669	128.904	138.095	122.130	119.589	135.579	105.393	103.233
Bank Control	NO	YES	YES	YES	YES	YES	YES	YES
Tranche Control	NO	NO	YES	YES	YES	-	-	-
Borrower × Month FE	YES	YES	YES	YES	YES	-	-	-
Lender Country-Borrower Country Pair FE	NO	NO	NO	YES	YES	NO	YES	YES
Tranche FE	NO	NO	NO	NO	NO	YES	YES	YES
Lender Country × Month FE	NO	NO	NO	NO	YES	NO	NO	YES
				First-Stage Results				
Initial GDP Growth Expectation	0.073***	0.076***	0.076***	0.071***	0.072***	0.075***	0.071***	0.072***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Effective F-Stat	1103.429	1113.277	1113.245	934.009	852.418	925.946	776.509	706.042

Notes: This table presents the two-stage least squares (2SLS) estimates of the baseline specification, using the imputed loan shares as the dependent variable. The upper panel shows the second-stage results, where the dependent variable is the imputed loan share (in percentage points) funded by a bank in the tranche, and the key explanatory variable is the instrumented bank's GDP growth expectation for the borrower's country, lagged by one period. The lower panel displays the first-stage results, where the dependent variable is the GDP growth expectation, and the key explanatory variable is the instrumental variable, i.e., the initial GDP growth expectation. The inclusion of control variables and fixed effects is as specified. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

The estimates indicate that an increase in growth expectations is significantly associated with an increase in the lender's loan share. The magnitude of the effect is smaller than in the baseline results, as the imputed shares are, on average, larger than the original ones. Specifically, a one standard deviation increase in growth expectations is associated with an increase in lender share of approximately 1.93 percentage points, or about 0.18 standard deviations of the imputed lender share.

We then replace the continuous growth expectation variable with a dummy indicating whether the expectation is above the consensus. Instead of examining the marginal

[10]The corresponding OLS results using the imputed lender shares are reported in Table A6 in the appendix, and the main findings remain robust.

effect of a one-unit increase in growth expectations, we test whether lenders with above-consensus expectations provide more credit than those with below-consensus expectations. Table 7 presents the results. As before, we use the initial forecast as the instrumental variable for the above-consensus dummy. The first-stage results indicate that higher initial forecasts are significantly associated with a greater likelihood of current expectations exceeding the consensus. The F-statistic confirms the strength of the instrument, alleviating concerns about weak identification. The second-stage results align with our baseline findings, showing that above-consensus expectations are associated with a 2.67 percentage point increase in loan share relative to below-consensus expectations.

Table 7: Robustness Check: Above or Below Consensus

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Second-Stage Results				
L.D(Above Consensus)	1.950***	1.386**	1.400**	1.851***	2.560***	1.468***	1.890***	2.668***
	(0.613)	(0.550)	(0.547)	(0.619)	(0.773)	(0.560)	(0.630)	(0.793)
Observations	27680	27680	27680	27680	27680	27680	27680	27680
F-Statistics	10.137	164.572	105.077	81.158	77.357	150.525	114.756	109.135
Bank Control	NO	YES	YES	YES	YES	YES	YES	YES
Tranche Control	NO	NO	YES	YES	YES	-	-	-
Borrower × Month FE	YES	YES	YES	YES	YES	-	-	-
Lender Country-Borrower Country Pair FE	NO	NO	NO	YES	YES	NO	YES	YES
Tranche FE	NO	NO	NO	NO	NO	YES	YES	YES
Lender Country × Month FE	NO	NO	NO	NO	YES	NO	NO	YES
				First-Stage Results				
Initial Forecast	0.174***	0.189***	0.189***	0.179***	0.173***	0.190***	0.179***	0.173***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.010)	(0.011)
R^2	0.513	0.518	0.518	0.527	0.623	0.519	0.529	0.624
F-Statistics	402.774	113.269	70.813	62.378	54.524	99.713	87.714	76.210

Notes: This table presents the two-stage least squares (2SLS) estimates of the baseline specification, using the above-consensus expectation dummy as the key explanatory variable. The upper panel shows the second-stage results, where the dependent variable is the loan share (in percentage points) funded by a bank in the tranche, and the key explanatory variable is the instrumented dummy indicating whether the bank's GDP growth expectation for the borrower's country is above the consensus, lagged by one period. The lower panel presents the first-stage results, where the dependent variable is the above-consensus GDP growth expectation dummy, and the key explanatory variable is the instrumental variable, i.e., the initial GDP growth expectation. The inclusion of control variables and fixed effects is as specified. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

Furthermore, we examine whether lead arrangers behave differently than the other lenders 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 lender's macroeconomic expectation in the baseline specification.[11] Table 8 presents the results. As before, we find that lenders' growth expectations have a significantly positive effect. Regarding the role of lead lenders, they do not appear to hold significantly different loan shares, but the effect of GDP growth expectations is significantly smaller for lead lenders compared to others. One possible interpretation (which corresponds to observable and known lending practices in the syndicate loan market) is that lead lenders may devote relatively more monitoring effort to firm-specific characteristics rather than to country-level macroeconomic conditions, compared to other lenders.

Table 8: Robustness Check: Role of Lead Lenders

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.GDP Growth Expectation	2.803**	1.927*	1.957*	2.676**	3.631**	2.079**	2.731**	3.817**
	(1.125)	(1.041)	(1.035)	(1.202)	(1.499)	(1.055)	(1.219)	(1.532)
L.GDP Growth Expectation × D(Lead Lender)	-1.518***	-1.660***	-1.604***	-1.665***	-2.030***	-1.621***	-1.690***	-2.093***
	(0.394)	(0.395)	(0.393)	(0.399)	(0.446)	(0.423)	(0.432)	(0.484)
D(Lead Lender)	-0.772	-0.183	-0.345	-0.215	0.311	-0.441	-0.295	0.300
	(0.843)	(0.842)	(0.837)	(0.854)	(0.958)	(0.931)	(0.955)	(1.081)
Observations	27680	27680	27680	27680	27680	27680	27680	27680
F-Statistics	79.408	142.236	101.776	83.393	79.293	133.554	109.065	103.673
Bank Control	NO	YES	YES	YES	YES	YES	YES	YES
Tranche Control	NO	NO	YES	YES	YES	-	-	-
Borrower × Month FE	YES	YES	YES	YES	YES	-	-	-
Lender Country-Borrower Country Pair FE	NO	NO	NO	YES	YES	NO	YES	YES
Tranche FE	NO	NO	NO	NO	NO	YES	YES	YES
Lender Country × Month FE	NO	NO	NO	NO	YES	NO	NO	YES

Notes: This table presents the two-stage least squares (2SLS) estimates of the specification, which additionally includes an interaction term between the bank's GDP growth expectation and a dummy variable indicating whether the bank is a lead lender. The dependent variable is the loan share (in percentage points) funded by a bank in the tranche, and the key explanatory variable is the instrumented 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. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

Next, we examine whether the impact of macroeconomic expectations varies with the level of uncertainty or disagreement among forecasters. Specifically, we compute the standard deviation of GDP growth forecasts for the same country-year made by different forecasters within the same month. A higher standard deviation indicates greater uncertainty about macroeconomic conditions. We then interact this standard deviation with lenders' expectations. Note that the coefficient on the standard deviation itself is

[11]More precisely, we classify lenders 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.

absorbed by the borrower country-month fixed effects. Table 9 presents the results. As before, lenders' growth expectations are significantly and positively associated with their credit supply. However, the interaction term with the uncertainty measure is insignificant. These findings suggest that forecast uncertainty does not materially alter the role of macroeconomic expectations in shaping credit supply.

Table 9: Robustness Check: Role of Uncertainty

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.GDP Growth Expectation	5.286***	3.332**	3.360**	4.664**	5.956**	3.625**	4.853**	6.428**
	(1.825)	(1.675)	(1.663)	(1.948)	(2.460)	(1.697)	(1.978)	(2.514)
L.GDP Growth Expectation × SD(L.GDP Growth Expectation)	-4.472	-1.757	-1.756	-2.776	-2.261	-2.109	-3.061	-2.891
	(2.740)	(2.586)	(2.565)	(3.014)	(3.610)	(2.603)	(3.047)	(3.659)
Observations	27680	27680	27680	27680	27680	27680	27680	27680
F-Statistics	5.086	137.630	93.795	72.661	69.733	125.903	96.146	91.955
Bank Control	NO	YES	YES	YES	YES	YES	YES	YES
Tranche Control	NO	NO	YES	YES	YES	-	-	-
Borrower × Month FE	YES	YES	YES	YES	YES	-	-	-
Lender Country-Borrower Country Pair FE	NO	NO	NO	YES	YES	NO	YES	YES
Tranche FE	NO	NO	NO	NO	NO	YES	YES	YES
Lender Country × Month FE	NO	NO	NO	NO	YES	NO	NO	YES

Notes: This table presents the two-stage least squares (2SLS) estimates of the specification, which additionally includes an interaction term between the bank's GDP growth expectation and the uncertainty of the consensus expectation, measured by the standard deviation of GDP growth forecasts across different forecasters. The dependent variable is the loan share (in percentage points) funded by a bank in the tranche, and the key explanatory variable is the instrumented 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. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

Next, one potential concern with our forecasting data is that some professional forecasters may not update their forecasts on a monthly basis, even though they continue to report to the Consensus Economics survey each month. To address this issue, we restrict the sample to cases where banks' forecasts differ from those of the previous month and repeat the baseline estimation. In other words, we examine the role of growth expectations only when a bank receives new information and actively updates its forecast. Table 10 presents the results. The findings reinforce the relationship between expectations and credit supply: a stronger GDP growth expectation is significantly associated with an increase in credit supply.

Table 10: Robustness Check: Subsample with Changed Expectation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.GDP Growth Expectation	3.313**	2.479**	2.529**	3.187**	3.459**	2.800**	3.436**	3.843**
	(1.339)	(1.226)	(1.219)	(1.331)	(1.567)	(1.239)	(1.351)	(1.592)
Observations	18826	18826	18826	18826	18826	18826	18826	18826
F-Statistics	6.119	117.761	73.886	56.116	53.113	108.827	81.485	77.214
Bank Control	NO	YES	YES	YES	YES	YES	YES	YES
Tranche Control	NO	NO	YES	YES	YES	-	-	-
Borrower × Month FE	YES	YES	YES	YES	YES	-	-	-
Lender Country-Borrower Country Pair FE	NO	NO	NO	YES	YES	NO	YES	YES
Tranche FE	NO	NO	NO	NO	NO	YES	YES	YES
Lender Country × Month FE	NO	NO	NO	NO	YES	NO	NO	YES

Notes: This table presents the two-stage least squares (2SLS) estimates of the baseline specification, limited to the sample where banks' forecasts differ from those of the previous month. 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 and instrumented by the initial forecast. The inclusion of control variables and fixed effects is as specified. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

5.4 Discussion

5.4.1 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. Table 11 presents the results from both OLS and 2SLS estimations. Interestingly, the inflation expectation is not significantly associated with the bank's loan share. In addition, we examine the roles of growth expectations and inflation expectations jointly. Table 12 presents the second-stage results of an augmented baseline regression that includes both GDP growth and inflation expectations, using their respective initial forecasts as instrumental variables. We continue to find a positive effect of growth expectations, with coefficient magnitudes comparable to those in the baseline results. As for inflation expectations, the results in the first column – where bank and tranche characteristics are not controlled for and granular fixed effects are omitted – suggest that higher inflation expectations are associated with a lower lender share. However, across the remaining columns, the coefficients on inflation expectations are statistically insignificant, consistent with the earlier findings when inflation expectations are analyzed in isolation.

Table 11: Inflation Expectation and Lender Share

	OLS		IV-2SLS	
	(1)	(2)	(3)	(4)
L.Inflation Expectation	-0.161	-0.234	0.591	0.735
	(0.320)	(0.328)	(1.132)	(1.161)
Observations	25140	25140	25140	25140
R^2	0.782	0.799		
F-Statistics	121.075	110.000	76.599	109.101
Bank Control	YES	YES	YES	YES
Tranche Control	YES	-	YES	-
Borrower × Month FE	YES	-	YES	-
Lender Country-Borrower Country Pair FE	YES	YES	YES	YES
Tranche FE	NO	YES	NO	YES
Lender Country × Month FE	YES	YES	YES	YES
			First-Stage Results	
Initial Inflation Expectation			0.118***	0.118***
			(0.004)	(0.004)
Effective F-Stat			809.168	711.318

Notes: This table presents the OLS and two-stage least squares (2SLS) estimates of the baseline specification, substituting the GDP growth expectation with the inflation expectation. 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 inflation expectation for the borrower's country, lagged by one period. Columns (1)-(2) display the OLS estimates. Columns (3)–(4) present the 2SLS results, where the key explanatory variable is instrumented by the initial inflation expectation, with the first-stage results reported in the lower panel. The inclusion of control variables and fixed effects is as specified. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

Table 12: GDP Growth and Inflation Expectation Together

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.GDP Growth Expectation	6.806***	3.561***	3.597***	4.418***	5.731***	3.666***	4.471***	5.980***
	(1.370)	(1.259)	(1.254)	(1.436)	(1.797)	(1.283)	(1.467)	(1.853)
L.Inflation Expectation	-5.106***	-0.890	-0.906	0.459	0.743	-0.730	0.556	0.915
	(1.022)	(1.065)	(1.061)	(1.040)	(1.140)	(1.087)	(1.066)	(1.171)
Observations	24949	24949	24949	24949	24949	24949	24949	24949
F-Statistics	20.426	127.039	86.122	68.493	64.335	116.234	91.270	85.531
Bank Control	NO	YES	YES	YES	YES	YES	YES	YES
Tranche Control	NO	NO	YES	YES	YES	-	-	-
Borrower × Month FE	YES	YES	YES	YES	YES	-	-	-
Lender Country-Borrower Country Pair FE	NO	NO	NO	YES	YES	NO	YES	YES
Tranche FE	NO	NO	NO	NO	NO	YES	YES	YES
Lender Country × Month FE	NO	NO	NO	NO	YES	NO	NO	YES

Notes: This table presents the two-stage least squares (2SLS) estimates of the specification, which includes both the bank's GDP growth expectation and inflation expectation simultaneously. The dependent variable is the loan share (in percentage points) funded by a bank in the tranche, and the key explanatory variable is the instrumented bank's GDP growth and inflation expectation for the borrower's country, lagged by one period. The inclusion of control variables and fixed effects is as specified. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

We interpret these results as reflecting the long maturity of syndicated loans, which average 4.2 years. Moreover, since all sample countries follow an inflation-targeting regime, inflation expectations should remain stable in the long run. As a result, short-term inflation is a less significant factor in banks' lending decisions. In contrast, it is crucial for banks that firms borrow during periods of favorable economic conditions, as assessed by the banks' own judgments regarding GDP growth.

5.4.2 Cross-border and Cross-currency Lending

In the baseline analysis, we do not distinguish between the nationality of the lender 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 lender and borrower are headquartered in different countries. We also define $D(\textit{In Lender Currency})$ and $D(\textit{In Borrower Currency})$ to indicate whether the loan is denominated in the lender's or borrower's domestic currency, respectively. In addition, we use $D(Offshore)$ to indicate that the deal currency is neither the lender's nor the borrower's domestic currency. We then interact these dummy variables with the lender's growth expectations in our baseline specification.

Table 13 presents the results. Columns (1)-(4) show that the effect of growth expectations does not significantly vary with whether the loan is cross-border or denominated in the lender's currency, as the interaction terms are statistically insignificant. Columns (5)-(6) suggest that when loans are not denominated in the borrower's currency, the lender's macroeconomic expectations for the borrower's country do not play a significant role. In other words, growth expectations significantly matter for credit supply when lending is denominated in the borrower's domestic currency. Moreover, in these cases, the magnitude of the effect is also more pronounced. Finally, columns (7)-(8) show that when the currency is neither that of the borrower nor the lender (i.e., offshore), the impact of growth expectations is not significantly altered.

Table 13: Cross-border and Cross-currency Lending

	Crossborder		In Lender Currency		In Borrower Currency		Offshore Currency	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.GDP Growth Expectation	5.201***	5.463***	4.945***	5.222***	1.877	-4.825	5.253***	5.521***
	(1.590)	(1.649)	(1.546)	(1.596)	(2.202)	(3.347)	(1.571)	(1.626)
L.GDP Growth Expectation × D(Crossborder)	6.848	7.056						
	(11.112)	(12.785)						
L.GDP Growth Expectation × D(In Lender Currency)			0.292	0.265				
			(0.200)	(0.192)				
L.GDP Growth Expectation × D(In Borrower Currency)					3.698*	11.533***		
					(2.040)	(3.803)		
L.GDP Growth Expectation × D(Offshore Currency)							-0.633	-0.713*
							(0.423)	(0.400)
Observations	27680	27680	27680	27680	27680	27680	27680	27680
F-Statistics	69.058	91.096	69.693	92.074	69.494	90.421	69.680	92.049
Bank Control	YES	YES	YES	YES	YES	YES	YES	YES
Tranche Control	YES	-	YES	-	YES	-	YES	-
Borrower × Month FE	YES	-	YES	-	YES	-	YES	-
Lender Country-Borrower Country Pair FE	YES	YES	YES	YES	YES	YES	YES	YES
Tranche FE	NO	YES	NO	YES	NO	YES	NO	YES
Lender Country × Month FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: This table presents the two-stage least squares (2SLS) estimates of the specification, which additionally includes an interaction term between the bank's GDP growth expectation and a dummy variable indicating either cross-border status or currency denomination. The dependent variable is the loan share (in percentage points) funded by a bank in the tranche, and the key explanatory variable is the instrumented 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. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

In summary, lenders' growth expectations regarding the borrower's country are particularly important for credit supply when the lending is denominated in the borrower's domestic currency.

5.4.3 Asymmetric Effects Between Positive and Negative Revisions

Bordalo, Gennaioli, and Shleifer (2018) demonstrate that credit cycles can be driven by diagnostic expectations, showing that agents tend to exhibit excessive optimism along a path of good news, often ignoring potential adverse outcomes. Building on this insight, we examine how growth expectations influence banks' credit supply in response to different types of news shocks, proxied by forecast revisions (Cascaldi-Garcia, 2024). Specifically, we compute forecast revisions as the change in GDP growth forecasts for the same country-year between the current and previous month. We classify a forecast revision as an optimistic news shock if it is positive, and as a pessimistic shock if it is negative. We then reestimate the baseline specification separately for these two subsamples.

Table 14 presents the results. We find that the effect of growth expectations on credit supply is more pronounced under optimistic news shocks. In particular, when banks receive positive news and revise their forecasts upward, those with higher growth expectations tend to expand credit supply more than those with lower expectations. In contrast, under pessimistic shocks – when forecasts are revised downward – a higher level of expectation does not significantly increase credit supply. This asymmetry is consistent with Bordalo, Gennaioli, and Shleifer (2018), who emphasize that credit expansion is disproportionately strong during sequences of favorable news.

Table 14: Asymmetric Effects: Positive and Negative News Shocks

	Positive Revision		Negative Revision	
	(1)	(2)	(3)	(4)
L.GDP Growth Expectation	7.883***	8.275***	0.776	1.131
	(3.044)	(3.177)	(1.815)	(1.812)
Observations	17605	16965	8442	7719
F-Statistics	46.883	59.167	20.198	29.834
Bank Control	YES	YES	YES	YES
Tranche Control	YES	-	YES	-
Borrower × Month FE	YES	-	YES	-
Lender Country-Borrower Country Pair FE	YES	YES	YES	YES
Tranche FE	NO	YES	NO	YES
Lender Country × Month FE	YES	YES	YES	YES

Notes: This table presents the two-stage least squares (2SLS) estimates of the baseline specification, splitting the sample into positive and negative forecast revisions. 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 and instrumented by the initial expectation. Columns (1)-(2) use the sample where the bank's GDP growth expectation for the current month and the same country-year is higher than or equal to that of the previous month. Columns (3)-(4) use the sample where the bank's GDP growth expectation for the current month and the same country-year is lower than that of the previous month. The inclusion of control variables and fixed effects is as specified. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

5.4.4 Heterogeneity Across Bank Characteristics

In addition, we explore potential heterogeneity across banks. Specifically, we interact the bank's GDP growth expectation with one of the following variables: bank size, measured by the natural logarithm of total assets; reversed leverage ratio, measured by the equity-to-asset ratio; and funding structure, measured by the ratio of depository funding to total assets. These variables are also included as control variables, as in the previous analyses.

Table 15 presents the results. We observe that the relationship between banks' macroeconomic expectations and loan shares varies with bank size and funding structure, but not with leverage. The smaller the bank and the less dependent it is on depository funding, the stronger the impact of expectations on credit supply. These findings suggest that smaller banks and those with less reliance on stable funding – who tend to be less diversified in their portfolios and face more volatile funding costs – are more aggressive or reactive in adjusting lending in response to changes in their economic expectations.

Table 15: Heterogeneous Effect Across Bank Characteristics

Bank Characteristics	Ln(Asset)		Equity/Asset		Depository Funding/Asset	
	(1)	(2)	(3)	(4)	(5)	(6)
L.GDP Growth Expectation	12.087***	12.032***	5.317***	5.529***	8.525***	8.742***
	(2.178)	(2.250)	(1.542)	(1.595)	(1.736)	(1.809)
L.GDP Growth Expectation × L.Bank Characteristics	-0.418***	-0.400***	-0.048	-0.035	-0.097***	-0.094***
	(0.125)	(0.130)	(0.054)	(0.054)	(0.013)	(0.014)
Observations	27680	27680	27680	27680	27680	27680
F-Statistics	70.401	93.339	69.911	92.312	73.603	96.725
Bank Control	YES	YES	YES	YES	YES	YES
Tranche Control	YES	-	YES	-	YES	-
Borrower × Month FE	YES	-	YES	-	YES	-
Lender Country-Borrower Country Pair FE	YES	YES	YES	YES	YES	YES
Tranche FE	NO	YES	NO	YES	NO	YES
Lender Country × Month FE	YES	YES	YES	YES	YES	YES

Notes: This table presents the two-stage least squares (2SLS) estimates of the specification, which additionally includes an interaction term between the bank's GDP growth expectation and a bank characteristics variable, including bank size measured by the natural logarithm of total assets, reversed leverage ratio measured by the equity-to-asset ratio, and funding structure measured by the ratio of depository funding to total assets, as indicated in the column headings. The dependent variable is the loan share (in percentage points) funded by a bank in the tranche, and the key explanatory variable is the instrumented 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. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

5.4.5 Bank-Borrower Country Aggregated Evidence

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

$$LoanTerm_{b,c,t} = \alpha_0 + \beta Expect_{b,c,t-1} + \alpha_1 Bank_{b,t-1} + \alpha_2 Loan_{b,c,t-1} + \delta_{c,t} + \lambda_{b',t} + \eta_{b',c} + \epsilon_{b,c,t} \quad (3)$$

Here, b, c, and t denote the bank, borrower country, and month, respectively. As before, we adopt an IV approach, using the initial GDP forecast as an instrument for current expectations. 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 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, while $Loan_{b,c,t-1}$ indicates lagged loan terms, including the outstanding loan amounts and other loan characteristics except for the current dependent variable. 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-time and bank country-borrower country fixed effects, respectively.

Table 16 presents the results. We find that a one standard deviation increase in the lender's expectation of GDP growth in the borrowing country is significantly associated with an 8.59 percentage point increase in the share of loans supplied by the lender, an 87.77% increase in the loan amount, a 163.38 basis point increase in borrowing costs, and a 30.46-month increase in loan maturity.[12] The findings on loan shares and amounts are consistent with our baseline results. The rise in borrowing costs aligns with D'Acunto, Gao, Liu, et al. (2025) and suggests that banks may be extending more credit to riskier

[12]Table A7 in the appendix reports summary statistics for the main variables in the bank-country-level dataset.

firms when they hold more optimistic expectations about the borrowing country.

Table 16: Bank-Country Aggregated Lending Terms

	Share		Ln(Amount)		Cost		Maturity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Second-Stage Results				
L.GDP Growth Expectation	7.063***	4.666***	1.082***	0.477*	92.044***	88.792***	14.999**	16.552**
	(2.076)	(1.747)	(0.386)	(0.272)	(30.183)	(30.345)	(7.100)	(7.142)
Observations	9684	9684	9684	9684	9684	9684	9684	9684
F-Statistics	11.573	194.148	7.880	398.702	9.299	5.350	4.463	8.657
Bank Control	NO	YES	NO	YES	NO	YES	NO	YES
Lending Terms Control	NO	YES	NO	YES	NO	YES	NO	YES
Borrower Country × Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Lender Country-Borrower Country Pair FE	NO	YES	NO	YES	NO	YES	NO	YES
Lender Country × Month FE	NO	YES	NO	YES	NO	YES	NO	YES
				First-Stage Results				
Initial GDP Growth Expectation	0.091***	0.091***	0.091***	0.091***	0.091***	0.091***	0.091***	0.090***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Effective F-Stat	76.940	76.430	76.940	76.430	76.940	76.249	76.940	76.083

Notes: The upper panel presents the two-stage least squares (2SLS) estimates of the specification, which regresses one of the four lending terms on banks' GDP growth expectations for the country, lagged by one period and instrumented by the initial expectation. The lower panel shows the first-stage results. The data are aggregated at the bank-country 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. The inclusion of control variables and fixed effects is as specified. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

6 Conclusion

In conclusion, our study demonstrates that global banks' macroeconomic expectations for borrower countries play a significant role in shaping their credit supply decisions. Using granular data on varying expectations among banks lending to the same firm at the same time and an instrumental variable approach, we find that more optimistic GDP growth expectations for a borrower country are strongly associated with increased credit supply. Specifically, a one standard deviation increase in a lender's GDP growth expectation for a borrower country leads to an 8.46 percentage point increase in the bank's loan share, which corresponds to an additional $75.35 million in lending to that country. These main findings remain robust across various checks.

Furthermore, we show that, compared to GDP growth expectations, global banks' short-term inflation expectations have no significant effect on their credit supply. In addition, the influence of their GDP growth expectations is particularly pronounced when loans are denominated in the borrower country's currency, during periods of positive news shocks, and among smaller banks and those with less reliance on stable funding. Lastly, beyond loan shares, the impact of macroeconomic expectations is also reflected in total lending amounts, costs, and maturities.

These findings have important policy implications. First, they highlight the critical role of global banks' expectations in driving credit cycles, suggesting that policymakers should monitor and assess the formation and dispersion of such expectations. Second, the strong influence of GDP growth expectations suggests that economic signaling and communication by governments and central banks can play a crucial role in attracting international credit. Ensuring transparency and reliability in macroeconomic forecasts can help bolster confidence among global lenders.

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Global Banks' Macroeconomic Expectations and Credit Supply

Online Appendix

A1 DealScan Data Clean 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 lender 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 lenders 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 lender 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 January 2022 (125,714 obs dropped)

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:

$$F_t x_{t+h} = (1-\lambda)E_t X_{t+h} + \lambda F_{t-1} x_{t+h} \tag{4}$$

full-information rational expectations are such that:

$$E_t x_{t+h} = X_{t+h} - v_{t+h,t} \tag{5}$$

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:

$$x_{t+h} - F_t x_{t+h} = \frac{\lambda}{1-\lambda}(F_t x_{t+h} - F_{t-1} x_{t+h}) + v_{t+h,t} \tag{6}$$

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:

$$x_t = \rho x_{t-1} + v_t \tag{7}$$

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

$$y_{it} = x_t + \omega_{it} \tag{8}$$

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

$$F_{it} x_t = G y_{it} + (1-G) F_{it-1} x_t \tag{9}$$

$$F_{it} x_{t+h} = \rho^h F_{it} x_t \tag{10}$$

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:

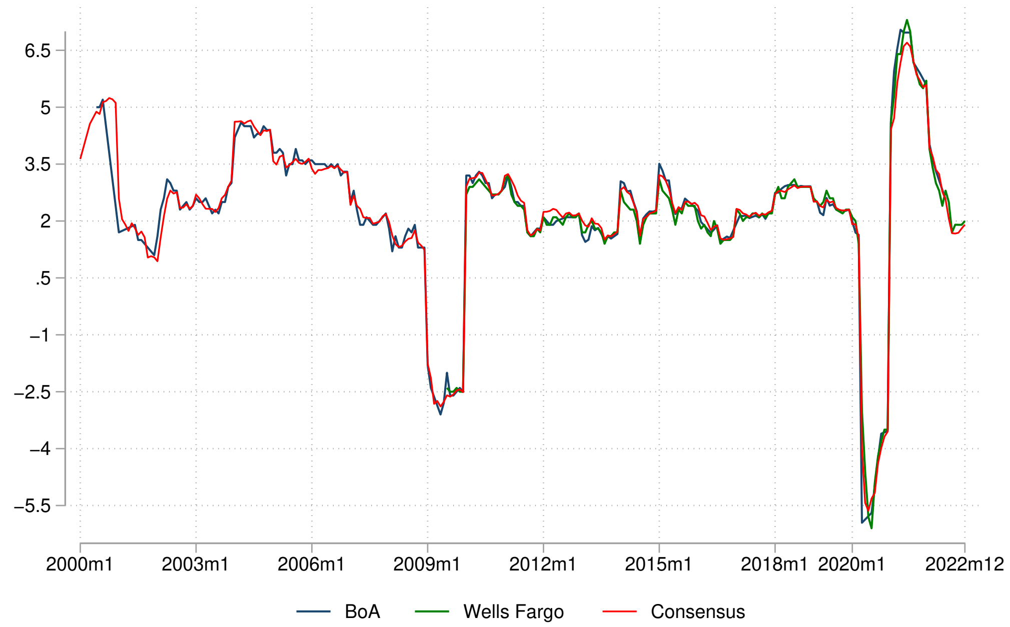
$$x_{t+h} - F_t x_{t+h} = \frac{1-G}{G}(F_t x_{t+h} - F_{t-1} x_{t+h}) + v_{t+h,t} \tag{11}$$

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:

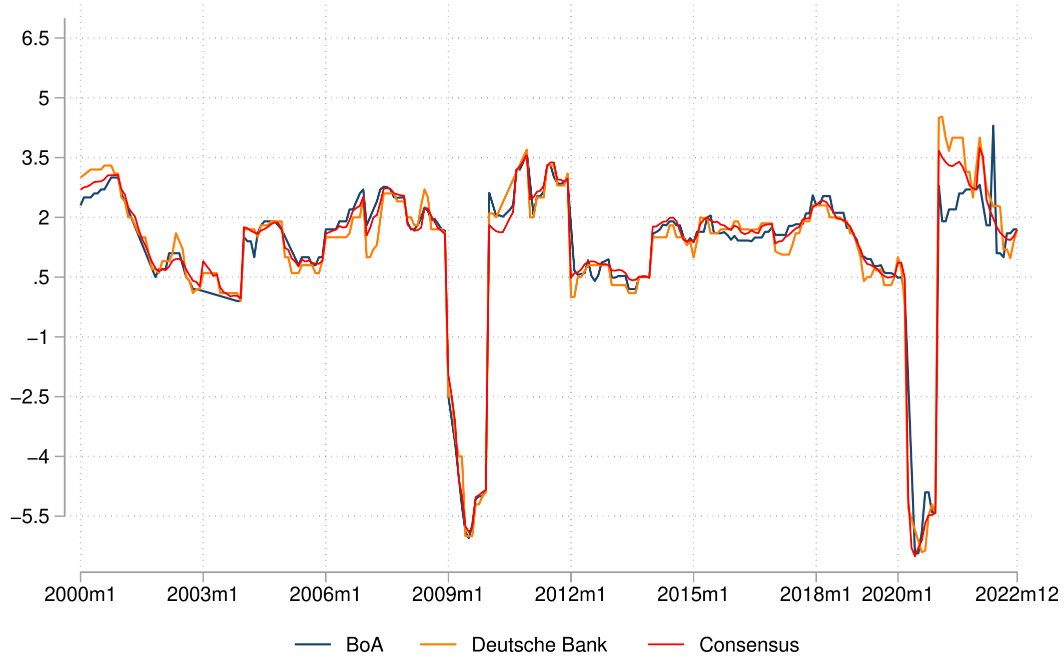
$$x_{t+h} - F_t x_{t+h} = c + \beta(F_t x_{t+h} - F_{t-1} x_{t+h}) + error_t \tag{12}$$

$\beta > 0$ 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



(a) US GDP Growth Expectation



(b) Germany GDP Growth Expectation

Figure A1: Examples of Banks' GDP Expectation for US and Germany

Notes: This figure shows the GDP growth forecasts of several example banks. The consensus is the average forecast across all institutions in the Consensus Economics database.

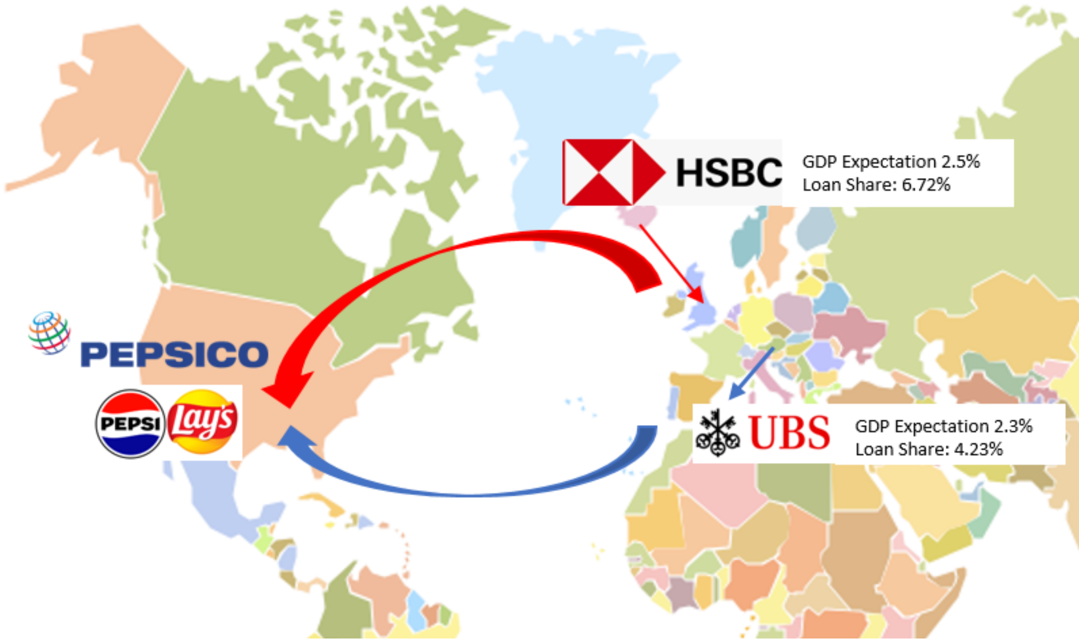


Figure A2: Illustration of the Loan Data

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.

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
Lender 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 Lenders	The number of lenders 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: Summary Statistics of Cleaned DealScan Data

	Mean	Standard Deviation	Min	Max	N
Lender Share (%)	15.431	19.741	0.460	100.000	411518
Observations With Non-Missing Lender Share					
Number of Lenders	12.499	9.845	1	170	411518
Ln(Tranche Amount)	4.972	1.702	-4.605	11.533	411518
Tranche Maturity (Month)	56.606	40.104	0	732	411518
Observations Including Missing Lender Share					
Number of Lenders	11.321	11.340	1	362	1405015
Ln(Tranche Amount)	4.899	1.673	-4.605	11.533	1405015
Tranche Maturity (Month)	57.831	38.631	0	969	1405015

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

Table A4: Comparing Banks with and without Forecast Data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D(Has Forecast)	2.054***	0.994***	0.983***	0.728***	0.715***	0.969***	0.725***	0.723***
	(0.098)	(0.099)	(0.098)	(0.105)	(0.121)	(0.097)	(0.104)	(0.120)
Consensus Forecast × D(Has Forecast)	-0.083**	-0.080**	-0.070**	-0.062*	-0.081**	-0.073**	-0.065*	-0.089**
	(0.035)	(0.034)	(0.034)	(0.034)	(0.040)	(0.033)	(0.034)	(0.040)
Observations	129707	129707	129707	129707	129707	129707	129707	129707
R^2	0.743	0.750	0.752	0.754	0.762	0.767	0.769	0.777
Bank Control	NO	YES	YES	YES	YES	YES	YES	YES
Tranche Control	NO	NO	YES	YES	YES	-	-	-
Borrower × Month FE	YES	YES	YES	YES	YES	-	-	-
Lender Country-Borrower Country Pair FE	NO	NO	NO	YES	YES	NO	YES	YES
Tranche FE	NO	NO	NO	NO	NO	YES	YES	YES
Lender Country × Month FE	NO	NO	NO	NO	YES	NO	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. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

Table A5: Summary Statistics of the IV Estimation Sample

	Mean	Standard Deviation	Min	Max	N
Lender Share (%)	12.782	11.343	0.460	100.000	27680
GDP Growth Expectation (%)	2.307	1.565	-6.566	7.400	27680
Ln(Asset)	13.231	1.770	7.428	21.276	27680
Equity/Asset	5.863	3.399	-2.145	111.449	27680
Depository Funding/Asset	64.741	21.886	0.291	187.897	27680
Ln(Outstanding Loans)	11.288	1.638	1.847	13.446	27680
Number of Lenders	13.533	9.114	1.000	156.000	27680
Ln(Tranche Amount)	5.710	1.615	-0.562	10.800	27680
Tranche Maturity (months)	51.196	30.048	1.000	444.000	27680

Notes: This table presents the summary statistics of the key variables used in the IV estimation.

Table A6: OLS Estimates: GDP Growth Expectation and Lender Share (imputed)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.GDP Growth Expectation	0.421***	0.394***	0.400***	0.401***	0.465***	0.392***	0.396***	0.469***
	(0.061)	(0.061)	(0.059)	(0.060)	(0.068)	(0.059)	(0.059)	(0.068)
L.Ln(Asset)		0.007	0.002	0.004	-0.012	-0.003	-0.010	-0.029*
		(0.015)	(0.014)	(0.014)	(0.017)	(0.012)	(0.013)	(0.015)
L.Equity/Asset		-0.012***	-0.011***	-0.015***	-0.017***	-0.009***	-0.010***	-0.010**
		(0.004)	(0.004)	(0.004)	(0.005)	(0.003)	(0.003)	(0.005)
L.Depository Funding/Asset		-0.004***	-0.004***	-0.004***	-0.005***	-0.004***	-0.004***	-0.006***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
L.Ln(Outstanding Loans)		0.409***	0.385***	0.406***	0.430***	0.384***	0.411***	0.435***
		(0.014)	(0.014)	(0.018)	(0.019)	(0.013)	(0.017)	(0.018)
Number of Lenders			-0.561***	-0.561***	-0.558***			
			(0.022)	(0.022)	(0.023)			
Ln(Tranche Amount)			0.021	0.021	0.022			
			(0.017)	(0.017)	(0.017)			
Tranche Maturity			-0.001	-0.001	-0.001			
			(0.001)	(0.001)	(0.001)			
Observations	184212	184212	184212	184212	184212	184212	184212	184212
R^2	0.896	0.896	0.901	0.901	0.902	0.922	0.922	0.923
Bank Control	NO	YES	YES	YES	YES	YES	YES	YES
Tranche Control	NO	NO	YES	YES	YES	-	-	-
Borrower × Month FE	YES	YES	YES	YES	YES	-	-	-
Lender Country-Borrower Country Pair FE	NO	NO	NO	YES	YES	NO	YES	YES
Tranche FE	NO	NO	NO	NO	NO	YES	YES	YES
Lender Country × Month FE	NO	NO	NO	NO	YES	NO	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, including imputed values for observations with missing loan shares. 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. Heteroskedasticity-robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1, 5 and 10% levels respectively.

Table A7: Summary Statistics of the Bank-Country Aggregated Sample

	Mean	Standard Deviation	Min	Max	N
Loan Share	6.977	6.127	0.007	50.000	9684
Ln(Amount)	5.879	1.497	-0.759	10.125	9684
Loan Cost	106.252	115.958	0.000	812.925	9684
Loan Maturity	50.406	23.629	0.000	421.208	9684
GDP Growth Expectation	1.836	1.839	-6.727	7.787	9684

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