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Banks' Inflation Expectations and Credit Allocation: the Fisher Effect

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Abstract

This paper investigates how lenders' inflation expectations shape credit allocation. Banks expecting higher inflation reallocate credit towards ex-ante leveraged firms, which benefit from a reduction in real debt burdens. To test this hypothesis, we combine individual bank macroeconomic forecasts for developed economies with syndicated loan data from 1991 to 2021. We show that banks expecting a 1 percentage point higher inflation over the next year extend loans that are 15% larger and 17 basis points cheaper to firms with high long-term leverage, relative to banks with lower inflation expectations. Importantly, the effects are not present for firms with high short-term leverage, whose real value is harder to reduce. Consistent with this pattern, firms receiving loans from banks with higher inflation expectations increase their capital expenditure relative to otherwise similar firms borrowing from banks with lower expectations.

Keywords: Inflation expectations, credit supply, Fisher effect

JEL: E31, E52, G21

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1 Introduction

Inflation erodes the real value of liabilities: as inflation rises, the real burden of debt falls. This is commonly referred to as the Fisher effect (Fisher, 1933).[1] Higher inflation reduces the default probability and interest expenses of indebted firms and increases their equity value relative to less-indebted firms (Brunnermeier et al., 2025). In other words, all else equal, highly leveraged firms are expected to perform better during inflationary periods. Anticipating this, banks with higher inflation expectations may reallocate credit towards firms with high leverage: a form of Fisher effect in credit allocation. While lenders' expectations are often thought to be an important driver of credit supply and financial crisis cycles (Minsky, 1977; Kindleberger, 1978; Greenwood and Hanson, 2013; Fahlenbrach et al., 2018; Carvalho et al., 2023), we know little about how they adjust lending in response to higher expected inflation.

This paper analyzes how lenders' inflation expectations influence their credit allocation across firms with different leverage levels. To test the Fisher hypothesis in credit allocation, we combine bank-level macroeconomic forecasts for developed countries from Consensus Economics with syndicated loan data from Loan Pricing Corporation (LPC Dealscan) and firm level data from Compustat from 1991 to 2021. We show that banks expecting higher inflation extend larger loans at lower rates to more leveraged firms, relative to banks with lower inflation expectations. Consistent with this pattern, firms receiving loans from banks with higher inflation expectations increase their capital expenditure relative to otherwise similar firms borrowing from banks with lower expectations.

Our main data source is the survey conducted by Consensus Economics, which collects monthly forecasts from banks and other institutions on key macroeconomic variables, including annual Consumer Price Index (CPI) inflation, GDP growth and interest rates (De Marco et al., 2022; Kalemli-Ozcan and Varela, 2021). Using the forecasters' names reported in Consensus Economics and lenders' names in LPC DealScan, we create a match

[1] Fisher's original paper discusses a deflationary environment in which the real value of debt increases.

between individual bank forecasts and loan data. This merge allows us to construct a bank-firm panel that links banks' macroeconomic forecasts for developed countries to their lending decisions for borrowers located in the same countries. We obtain firm-level financial data from Compustat Global and North America, which we merge with the Consensus Economics–LPC DealScan database using the linking file provided by Chava and Roberts (2008). The final dataset contains over 21,000 syndicated loan-deals from the United States, Europe, and Japan (i.e., G7 plus other European countries), spanning the period from 1991 to 2021.

In the baseline specification, we regress the (log of the) credit line amount and the interest rate spread over a risk-free variable rate (e.g., LIBOR) on banks' inflation expectations for the following year (i.e., annual CPI growth), firm leverage from the previous year and their interaction. Our credit-Fisher hypothesis is that the coefficient on the interaction term between bank CPI forecasts and firm leverage is positive on credit amounts and negative on interest rate spreads, i.e. a credit supply expansion. The specification includes a rich set of fixed effects at the firm, country-month and industry-by-year level. Country-month fixed effects ensure that our estimates capture the bank-specific variation from the average CPI forecast for a given country in a given month vis-à-vis other banks. In other words, in the empirical analysis we exploit only variation from the average bank forecast rather than the level of CPI. The estimates are therefore not reflecting a simple comparison of periods of high vs. low inflation, but rather bank-specific expectations of higher than average inflation in a country.

Quantitatively, we show that a bank expecting one percentage point higher inflation for the next year extends, on average, 15% more credit in the form of credit lines and charges a 17.5 basis points lower spreads to highly leveraged firms (i.e., those at the 90^{th} percentile of the leverage distribution), compared to a bank expecting lower inflation. While firms with high leverage receive on average less credit than others, a bank expecting one percentage point higher inflation closes about 40% of this financing gap. Similarly, while highly leveraged firms pay higher interest rate spreads, banks expecting higher inflation close about one third of this gap. This pattern is consistent with banks internalizing the Fisher effect: firms with higher leverage benefit in an inflationary environment and credit supply is redirected towards them. The decrease in interest rates provides a supply-side interpretation to the findings in Brunnermeier et al. (2025), who show that firms with high ex-ante leverage have a lower share of interest expenses during high inflation.

Crucially for our purposes, Compustat data distinguish between long-term and short-term debt. Long-term debt, i.e., debt with a maturity greater than one year, is typically issued at fixed rates (e.g., bonds) and hence its real value is more easily eroded by inflation. Short-term debt instead adjusts more frequently (e.g., bank credit lines) and its value is therefore harder to reduce in real terms (Gomes et al., 2016). Accordingly, we find that banks with higher expected inflation reallocate credit only towards firms with high long-term leverage, not to those with high short-term leverage. Moreover, including the interaction between banks' inflation expectations and short-term leverage in our baseline specification leaves the coefficient on the interaction between long-term leverage and inflation expectations unchanged. This supports the idea that banks expecting higher inflation primarily consider the portion of debt that is more exposed to inflation when making lending decisions.

Additionally, we find that banks expecting higher inflation do not lend at longer maturities to firms with higher long-term leverage. Instead, they reduce the maturity of the credit extended to these firms. This is the result of the expansion of credit lines, both in terms of amounts and lower interest rate spreads, rather than term loans, which effectively lowers the average maturity of credit given to these firms. This is in line with Agarwal and Baron (2024), who show that inflation-exposed banks shorten the maturity of their portfolios by reducing their long-term nominal lending and rebalancing towards new shorter-maturity lending. It suggests that banks with higher inflation expectations change the composition of credit to high-leverage firm, in an attempt to attenuate their exposure in the long run.

We address several potential concerns regarding the interpretation of our results. For instance, bank inflation forecasts are correlated with other forecasts, such expectations about future monetary policy rates, long-term interest rates and future GDP growth, and it is likely that these alternative forecasts jointly drive both inflation expectations and lending decisions. Since Consensus Economics provides forecasts for various macroeconomic variables, including short-term (3month), long-term (10-year) interest rates, and GDP growth, we are able to include these controls, and their interaction with firms' long-term leverage, directly in the estimation. We find that the main coefficient of interest remains statistically significant and of similar magnitude. We also show that our results are robust to additional controls, geographic subsamples, and alternative time periods.

In the last part of the paper, we examine the real effects of banks' lending decisions. A firm with high long-term leverage (i.e., 90^{th} percentile) that borrows from a bank expecting one percentage point higher inflation for the following year increases its capital expenditure by 8% relative to an otherwise similar firm borrowing from a bank with lower inflation expectations. It is worth noting that borrowing from a bank that expects higher inflation has a stronger effect on high long-term leverage firms investment decision than borrowing from a bank that expects higher GDP growth, another driver of bank lending decisions (Li and Ongena, 2025).

This paper contributes to three strands of the literature. A growing literature documents that beliefs and portfolio choices are aligned at the individual level, both for retail and institutional investors (Giglio et al., 2021; Beutel and Weber, 2022; De Marco et al., 2022). In the context of credit markets, Ma et al. (2021) show that US banks with pessimistic house price expectations lend less to local firms. D'Acunto et al. (2024) provide experimental evidence from China that exogenous shifts in macroeconomic expectations, such as inflation and GDP growth, influence loan officers' decisions. However, little is known about whether, and how, bank-specific inflation expectations affect the allocation of credit across firms with different debt structures.[2] This paper fills that gap by providing new evidence from the syndicated loan market, one of the largest credit markets worldwide.

A large theoretical literature suggests that inflation, by eroding the real value of nominal debt, benefits borrowers (Keynes, 1923; Fisher, 1933; Gomes et al., 2016). Empirical evidence for this channel has emerged only recently. Brunnermeier et al. (2025) show that German hyperinflation in 1920s reduced the default probability and interest expenses of highly indebted firms, increasing both their book and market values. Using the recent Covid-induced inflation hike, D'Andrea et al. (2025) similarly show that firms with higher leverage increase their market value during inflationary periods. Agarwal and Baron (2024) exploit differences in state-level reserve requirements in the 1970s to show that unexpected increases in inflation reduce bank lending. We contribute to this literature by showing that banks internalize these effects when forming lending decisions. Specifically, we find that banks expecting higher inflation extend larger credit lines at lower interest rates to firms with high long-term leverage, relative to banks with lower inflation expectations.

Finally, an extensive literature documents the effects of inflation on real variables such as investment, consumption, and growth (Barro et al., 1996). However, there is less evidence on its transmission through bank balance sheets, despite this channel being well established in the context of monetary policy shocks (Kashyap and Stein, 2000; Jiménez et al., 2012, 2014). It has also been shown that firm characteristics matter for their investment response to such shocks (Ottonello and Winberry, 2020; Jeenas, 2023). We show that inflation also operate through this channel: changes in expected inflation shift banks' credit allocation toward firms with higher long-term leverage, which in turn affects these firms' investment decisions.

This paper is structured as follows. Section 2 describes the main data sources. Section 3 introduces the baseline specification and presents the main results, addressing alternative

[2] Li and Ongena (2025) show that higher GDP growth expectations increase credit supply, but inflation expectations do not. We also confirm that inflation expectations do not affect credit supply for the average firm, but only for those with high long-term leverage.

interpretations. Section 4 shows that the results are entirely driven by firms' long-term leverage, while short leverage does not play a significant role. Section 5 shows that firms borrowing from banks with higher inflation expectations also increase their capital expenditures. Section 6 concludes.

2 Data

Our empirical analysis combines data from multiple sources: individual bank-level macroeconomic forecasts from Consensus Economics; syndicated loan characteristics from LPC DealScan; and firm-level balance sheet information from Compustat.

Our primary data source is Consensus Economics, a monthly survey of professional forecasters. The panel includes participants from a range of institutions, including banks' macroeconomic research departments. At the start of each month, Consensus Economics collects forecasts for several macroeconomic variables, which are released publicly in the second week of the month. The survey covers 24 countries mainly advanced economies, including the G7 and other Western European countries, from October 1989.[3] The main variable we use is the inflation forecast for the following calendar year (i.e., annual CPI growth expected at the end of the next year), but we also use as controls GDP growth, short-term and long-term interest rates forecasts.

Forecasts are submitted by both domestic and foreign institutions. Over the sample period, we observe 340 unique forecasters, including 137 banks. Among them, 41 are large global banks from the US, EU, and Japan, while others are smaller regional players that do not appear on LPC Dealscan. Table A1 in Appendix 1 presents the list of 26 banks that make at least 200 forecasts over the sample period. The biggest global banks such as Bank

[3]Coverage begins in October 1989 for seven countries, including the United States, which accounts for the largest number of syndicated loans in the LPC DealScan sample. Currently, Consensus Economics covers the following countries: Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Japan, Ireland, Egypt, Israel, Italy, Netherlands, Nigeria, Portugal, Saudi Arabia, South Africa, Spain, Sweden, Switzerland, UK, USA.

of Tokyo-Mitsubishi, JP Morgan, Bank of America, and their predecessors, like Nations Bank, Wachovia are among the most frequent contributors. Among US and Japanese banks there is a high degree of home bias, as the top target country of their forecasts is the country where they are headquartered, whereas UK and Swiss banks produce forecasts for a wider range of foreign countries, which typically includes the United States.

A key feature for our purposes is the substantial dispersion in banks' 1-year ahead inflation forecasts. In particular, we exploit variation across banks forecasting inflation for the same country in the same month. Figure 1 plots the standard deviation of the residuals from a regression of individual bank forecasts on country-month fixed effects. That is, we control for the average forecast in each country-month and examine the cross-sectional dispersion around that country-time mean. Even conditional on forecasting the same country in the same month, the standard deviation of CPI forecasts ranges from approximately 0.1 to 0.5 percentage points. This is a large variation considering that the average 1-year ahead CPI forecasts during the sample period is 1.87%. For our results identification we exploit this bank forecast heterogeneity in inflation forecast within each country and month.

A key advantage of the Consensus Economics data is that it discloses the identity of individual forecasters, allowing us to link forecasts to lender-level information. We match bank-level inflation forecasts from Consensus Economics to syndicated loan data from LPC DealScan, a comprehensive database of loans extended to large firms by bank syndicates. The matching relies on bank names reported in both datasets. As a contribution, we also provide a bank name matching file between the two sources. Appendix 1 describes the matching procedure in detail. Since there are typically many lenders in a deal, the lenders' expectation for each deal is the simple average of the individual forecasts if more than one is present in both Conensus and LPC Dealscan.

The LPC DealScan data include key loan characteristics such as spreads, fees, maturity, amount, facility type, collateral, and covenants. The database also reports the country of both borrowers and lenders. The dataset covers all syndicated loans issued by public and private firms starting in 1991. For each syndicated loan, we observe information at the facility level. The two main facility types are term loans and credit lines.[4] Our primary loan pricing variable is the interest rate spread, denoted as $Spread$, which measures the spread borrowers pay over a benchmark rate (e.g., LIBOR).[5]

We collect firm-level financial data from Compustat North America and Compustat Global, which provide annual balance sheet information for firms headquartered in North America and in the rest of the world, respectively (hereafter we refer to both sources jointly as Compustat). The dataset includes information on debt, assets, capital expenditures, and other key variables. In particular, Compustat distinguishes between short-term debt (due within one year) and long-term debt (due after one year). Long-term debt is typically not indexed to inflation, while short-term debt is more likely to be adjusted or renegotiated in response to short-term inflationary pressures. To account for these differences, we define short-term leverage as short-term debt over total assets, and long-term leverage as long-term debt over total assets. If the mechanism driving our results operates through the real burden of debt, consistent with the Fisher effect, we expect the impact to be concentrated in long-term leverage rather than short-term leverage.

We merge the Consensus Economics–DealScan dataset with Compustat using the DealScan–Compustat Linking Database from Chava and Roberts (2008). To construct the final sample, we follow standard procedures from the literature. First, since banks play different roles within loan syndicates (Ivashina, 2005), we exclude from the sample banks whose role in deal is classified as "participant." [6] Second, we exclude firms in the financial, real estate, and insurance sectors (SIC codes 6000–7000). Finally, we drop loan amendments, which are often misclassified in DealScan as new loans, even though they may not involve

[4]A deal typically includes multiple facilities. The two main types are revolving credit lines—where firms can draw funds on demand—and term loans, in which the firm receives a pre-arranged amount of money up front. Term loans include Term A, Term B, and other long-term structures.

[5]Borrowers may also incur additional charges. The second most relevant is the fee on drawn amounts, denoted as $margin$.

[6]Results are similar when limiting the sample to lead arrangers only.

additional funding (Roberts, 2015).

The resulting dataset contains over 21,000 deals between 1991 and 2021.[7] Most deals involve US (64.7 percent), Japan (20.7 percent), EU (8.6 percent), or UK firms (5.5 percent). Each deal may include multiple loan facilities, with credit lines being the most common, accounting for almost 17,000 facilities, and term loans the second most common with around 7500 facilities. Credit lines are particularly important for firms as they provide access to liquidity on demand (Acharya et al., 2014; Cooperman et al., 2025).

Table 1 reports summary statistics of the main variables used in the empirical analysis. Panel A presents forecast data from Consensus Economics, including inflation, short and long term interest rate, and GDP growth expectations for the end of the following year. Panel B displays deal-level variables from LPC DealScan, such as loan amount, spread, and maturity. Panel C reports firm-level variables from Compustat, including short and long-term leverage.

3 Empirical Strategy and Baseline Results

We examine whether banks that expect higher inflation for the following year adjust their lending behavior based on firms' long-term leverage. In this section, we focus on credit lines, the most common facility type, which offer a more homogeneous basis for comparison across countries compared to the full deal.[8] Our baseline specification is:

$$\begin{aligned} L_{b,f,c,k,t} = {} & \beta_1 long\ Lev_{f,y-1} + \beta_2 CPI^f_{b,c,t} + \beta_3 CPI^f_{b,c,t} \times long\ Lev_{f,y-1} \\ & + \omega_{c,t} + \omega_f + \omega_{k,y} + \chi_{f,y-1} + \epsilon_{b,f,c,k,t}, \end{aligned} \tag{1}$$

where $L_{b,f,c,k,t}$ denotes a credit outcome, either the log of the credit line amount or the spread (over the benchmark interest rate, typically the LIBOR), between bank b and firm

[7]The Chava and Roberts (2008) link extends through 2021.

[8]Appendix 2 reports similar results for the full loan package.

f, located in country c and operating in sector k, in month t. The variable $CPI^{f}_{b,c,t}$ is the bank-level forecast for the end-of-next-year inflation (i.e., annual year-end CPI growth) for country c, produced by bank b at month t. The term $long\ Lev_{f,y-1}$ captures firm f's long-term leverage in the previous year ($y-1$). $GDP^{f}_{b,c,t}$ represents the bank's forecast of one-year-ahead GDP growth (i.e., the expected growth rate for the following calendar year).

Given the presence of country month fixed effects $\omega_{c,t}$, the coefficient on $CPI^{f}_{b,c,t}$ (and on $GDP^{f}_{b,c,t}$) captures the bank-specific variation from the mean forecast for the country vis-à-vis other banks. Figure 1 shows there is significant variation across banks throughout the whole time period. This is the variation that we exploit in our empirical analysis. Importantly, we do not compare high vs. low inflationary periods, but only bank-specific expectations of higher inflation. Finally, ω_f denote firm fixed effects, to absorb time-invariant unobserved firm characteristics, including their preference for high leverage, and $\omega_{k,y}$ represent two digit (SIC Code) industry year fixed effects, to control for industry-time varying shocks.

The main coefficient of interest is β_3, which captures the effect of the interaction between the bank's inflation forecast, $CPI^{f}_{b,c,t}$, and the firm's lagged long-term leverage, $long\ Lev_{f,y-1}$. Under the hypothesis that banks internalize the Fisher effect, anticipating that inflation reduces the real burden of nominal debt, we expect a positive coefficient when the dependent variable is the logarithm of the loan amount, and a negative coefficient when the dependent variable is the spread. While a negative relationship between inflation expectations and loan spreads might appear counterintuitive, since one might expect higher inflation expectations to lead to higher nominal interest rates, our focus is on interest rate spreads relative to a reference rate, rather than on the absolute level of interest rates. The reference rate itself is likely to rise with expected inflation, as it reflects broader macroeconomic conditions (Cooperman et al., 2025).

We also include bank-level forecasts of GDP growth as controls, since expected output growth may correlate with inflation expectations and influence lending behavior (Li and Ongena, 2025). In addition, we control for firm-level observable characteristics and their interaction with bank inflation forecasts, to account for the possibility that these characteristics are related to both firm leverage and banks' lending decisions. $\chi_{f,y-1}$ includes firm-level controls, such as lagged profitability and tangibility.

Table 2 reports the results from estimating Equation 1, using the log of the credit line amount as the dependent variable. The coefficient on the interaction term shows that banks with higher inflation expectations tend to extend larger credit lines to firms with higher long-term leverage, relative to banks with lower inflation expectations. The coefficient remains similar in magnitude and statistically significant across specifications as additional controls are introduced in each column. In the main specification (column 4), the estimate implies that a bank expecting inflation to be 1 percentage point higher lends about 15% more to a firm with high leverage (i.e., long-term leverage over total assets equal to 0.5, or the 90^{th} percentile) than a bank expecting inflation to be 1 percentage point lower ($0.31 \times 0.50 = 0.155$). The control variables on GDP growth exhibit signs consistent with economic intuition: banks forecasting stronger GDP growth tend to lend larger amounts, although not specifically to highly leveraged firms.

Quantitatively, another way to interpret our estimates is to compare them to the average financing gap of leveraged firms. The coefficient on long-term leverage shows that firms with high leverage receive lower credit line amounts, but a bank expecting one percentage point higher inflation closes about 40% of this financing gap (0.31/0.74=0.41).

Table 3 reports the results from estimating Equation 1, using the credit line spread as the dependent variable. The first row shows that banks with higher inflation expectations charge lower spreads to firms with higher long-term leverage, relative to banks with lower inflation expectations. In economic terms, our preferred specification (column 4) implies that a bank expecting inflation to be 1 percentage point higher charges a spread 17.5 basis points lower to a high leverage (i.e., 90^{th} percentile) firm than a bank expecting inflation to be 1 percentage point lower ($0.35 \times 0.50 = 0.175$). This effect represent 15% of the average spread on credit lines during the sample period, so it is substantial. Compared to the 50% higher spread faced by firms with high leverage, banks expecting one percentage point higher inflation reduce about one third of this financing gap (35/106=0.33).

The results are consistent with banks internalizing the Fisher effect. Appendix 2 shows that these findings also hold at the deal level and are robust across time periods (before and after the 2007 financial crisis) and countries (US and Japan, which had very different inflation trajectories since the 1990s). The results are also robust to adopting a stricter definition of the main deal arranger, such as the one proposed by Ivashina (2005), and to including amended deals in the sample. In addition, Appendix 2 reports similar results for other interest rates in the credit line facility.

3.1 Lending More and Cheaply, but with Shorter Maturity

This section examines whether banks with different inflation expectations also adjust the maturity of the credit line they extend to firms with varying levels of long-term leverage. Agarwal and Baron (2024) argue that higher expected inflation volatility induces banks to shorten the maturity of their loan portfolio and reallocate their assets away from long-term nominal loans and toward inflation-protected assets, such as short-term variable C&I loans. They label this mechanism the loan misallocation channel. Similarly, we find that banks expecting higher inflation do not offer longer maturities to more long-term leveraged firms. On the contrary, they tend to slightly reduce the maturity of credit lines granted to these firms. This pattern is consistent with banks seeking to limit their long-term exposure to firms with higher leverage.

To analyze this mechanism, we estimate a specification analogous to Equation 1, using the maturity of the credit line (measured in months) as the dependent variable. The main coefficient of interest is the interaction between bank inflation forecast, $CPI^{f}_{b,c,t}$ and firm lagged long-term leverage, $long\ Lev_{f,y-1}$. The specification includes the same set of controls as in Equation 1.

Table 4 reports the results. Banks with higher inflation expectations tend to offer shorter maturities to firms with higher long-term leverage. The coefficient of interest becomes larger in absolute value and more statistically significant as additional controls are included. In our preferred specification (column 4), a bank expecting inflation to be one percentage point higher reduces the maturity of the credit line to a highly leveraged firm by approximately two months relative to a bank expecting one percentage point lower inflation. Note that a two-month reduction represents a 5% decrease relative to the average credit line maturity of nearly 39 months. This result is not specific to credit lines. Appendix 2 shows that banks expecting higher inflation also shorten the maturity of other facilities within the deal.

3.2 Robustness

The results from Table 2 and Table 3 indicate that banks with higher inflation expectations extend larger credit lines and charge lower spreads to firms with higher long-term leverage, relative to banks with lower inflation expectations. While these findings are consistent with banks internalizing the Fisher effect, there are potential alternative interpretations, which we address in this section.

A potential concern is that banks' inflation forecasts may be influenced by broader macroeconomic expectations, such as anticipated monetary policy, that could also affect lending behavior. To address this, we directly control for monetary policy expectations in the regression. Specifically, Consensus Economics provides forecasts of short-term interest rates and ten-year sovereign bond yields.[9] Equation 2 presents the extended specification, which includes a bank-level interest rate forecast variable, int, representing either the forecasted three-month interest rate, $3\text{-}M^f$, or the ten-year sovereign bond yield, $Y10^f$. These forecasts enter the regression both directly and interacted with the firm's lagged

[9] Appendix 1 shows how these bank interest rates forecast evolve over time and their relationship with bank inflation forecast.

long-term leverage:

$$L_{b,f,c,k,t} = \beta_1 long\ Lev_{f,y-1} + \beta_2 CPI^f_{b,c,t} + \beta_3 CPI^f_{b,c,t} \times long\ Lev_{f,y-1} + \alpha_1 GDP^f_{b,c,t} + \alpha_2 GDP^f_{b,c,t} \times long\ Lev_{f,y-1}$$
$$+ \alpha_3\ M3_{b,c,t} + \alpha_4 M3_{b,c,t} \times long\ Lev_{f,y-1} + \alpha_5\ Y10_{b,c,t} + \alpha_6 Y10_{b,c,t} \times long\ Lev_{f,y-1} + \omega_{c,t} + \omega_f + \omega_{k,y} + \epsilon_{b,f,c,k,t} \tag{2}$$

Table 5 presents the results from estimating Equation 2. Columns 1 and 2 report estimates using the logarithm of the credit line amount as the dependent variable, while Columns 3 and 4 focus on the spread. Columns 1 and 3 include the forecasted three-month interest rate, 3-M^f, while Columns 2 and 4 include the ten-year sovereign bond yield, $Y10^f$. In both cases, we include the interaction between the interest rate forecast and the firm's lagged long-term leverage.

Across all specifications, the interaction between banks' inflation forecasts and firm leverage remains statistically significant and similar in magnitude to the main results shown in Tables 2 and 3. Moreover, forecasts of short-term interest rates and ten-year sovereign bond yields do not substantially alter the results and are generally not significant predictors of lending terms. One possible explanation is that, for most of the sample period, credit lines were priced over LIBOR, which adjusts to prevailing macroeconomic conditions. As a result, expectations about macroeconomic policy may already be reflected in the benchmark rate used to price loans (Cooperman et al., 2025).[10]

The two most commonly reported forecasts in the Consensus Economics sample are GDP growth and inflation. In contrast, fewer banks provide forecasts for sovereign bond yields and short-term interest rates. As a result, the sample size in Table 5 is smaller than in Tables 2 and 3.

Another potential concern is that banks expecting higher inflation may systematically lend more to firms in specific sectors, particularly those that both benefit from rising prices

[10]Banks' inflation and interest rates forecasts are less correlated than one might expect. On average, the coefficient of correlation between banks' inflation and interest rates forecasts is below 0.25. Figures A2, A3 and A4 in Appendix 1 show the correlation over time between these forecasts.

and may tend to be more leveraged. For example, if the inflation surge is driven by oil prices, banks anticipating higher inflation may increase lending to energy-related firms, which may also exhibit higher long-term leverage. Our baseline specification already includes two-digit industry-by-year fixed effects to account for sectoral composition. To further address this concern, we refine the baseline specification (Equation 1) by incorporating (1-digit)industry-by-country–month fixed effects, thereby comparing firms within the same sector and country in the same month.[11]

$$
\begin{aligned}
L_{b,f,c,k,t} = {} & \beta_1 long\ Lev_{f,y-1} + \beta_2 CPI^f_{b,c,t} + \beta_3 CPI^f_{b,c,t} \times long\ Lev_{f,y-1} \\
& + \omega_f + \omega_{k,t,c} + \chi_{f,y-1} + \chi_{f,y-1} \times CPI^f_{b,c,t} + \epsilon_{b,f,c,k,t},
\end{aligned} \tag{3}
$$

Since Equation 3 includes industry-month-country FE ($\omega_{k,t,c}$), we do not need to introduce country-month FE ($\omega_{c,t}$) as Equation 1.

Table 6 reports the results from this extended specification. Column 1 uses the log amount of the credit line as the dependent variable, and Column 2 uses the spread. The coefficient of interest, the interaction between the bank's inflation forecast and the firm's lagged long-term leverage, remains statistically significant and similar in magnitude to the baseline estimates.

At the industry level, some country–month cells contain fewer than two firms receiving syndicated loans. As a result, the sample size in this specification drops by over one thousand observations compared to the baseline. Therefore, comparisons should be interpreted with caution.

[11] In this case, we introduce one-digit industry fixed effects. Two-digit industry-by-month-by-country fixed effects is too restrictive and the sample would be reduced considerably.

4 Short vs long-term leverage

As previously discussed, there is a crucial distinction between long- and short-term corporate debt. It is well known (Gomes et al., 2016) that long-term debt is generally easier to reduce its real value in an inflationary environment, as it typically carries fixed interest rates and does not adjust quickly to rising inflation. In contrast, short-term debt usually is easier to adjust, making it harder for firms to reduce their debt burden when inflation increases. Therefore, the effect we observe for long-term leverage should not apply to short leverage (short-term debt over total assets). To test this, we re-estimate the baseline specification from Equation 1, adding short-term leverage and its interaction with bank inflation and GDP growth forecasts as additional controls,

$$\begin{aligned} L_{b,f,c,k,t} = {} & \beta_1 long\ Lev_{f,y-1} + \beta_2 CPI^f_{b,c,t} + \beta_3 CPI^f_{b,c,t} \times long\ Lev_{f,y-1} + \alpha_0 short\ Lev_{f,y-1} + \alpha_1 CPI^f_{b,c,t} \times short\ Lev_{f,y-1} \\ & + \gamma_1 GDP^f_{b,c,t} + \gamma_2 GDP^f_{b,c,t} \times long\ Lev_{f,y-1} + \gamma_3 GDP^f_{b,c,t} \times short\ Lev_{f,y-1} \\ & + \omega_{c,t} + \omega_f + \omega_{k,y} + \chi_{f,y-1} + \chi_{f,y-1} \times CPI^f_{b,c,t} + \epsilon_{b,f,c,k,t}. \end{aligned} \tag{4}$$

Table 7 reports the results from estimating Equation 4. Panel A presents results using the log amount as the dependent variable, while Panel B focuses on the spread. Each column includes additional controls as in Section 3.

Across all specifications, the interaction between long-term leverage and bank inflation forecasts remains statistically significant and similar in magnitude to the baseline results. In contrast, the interaction between short leverage and bank inflation expectations is not statistically significant for either outcome. In some specifications, such as those in Panel A, the coefficient even has the opposite sign to that of long-term leverage. These findings suggest that lenders differentiate across debt types when interacting with their inflation expectations: only long-term leverage, whose real value is more affected by inflation, systematically influences credit decisions in response to expected inflation. These results are consistent with Brunnermeier et al. (2025) and D'Andrea et al. (2025), who show that only long-term debt affects a firm's market value in an inflationary environment, while short-term debt has no significant effect.

5 Effect on the Real Economy

Changes in credit conditions typically have a direct impact on firms' investment decisions. From a textbook perspective, access to more and cheaper credit can make a broader range of investment projects financially viable. We therefore expect that highly long-term leveraged firms borrowing from banks with higher inflation expectations will increase their capital expenditures. To test this hypothesis, we estimate a specification analogous to the one from the previous section, using the logarithm of capital expenditures in the following year, $log\ Cap\ Exp_{f,c,y+1}$, as the dependent variable.

Table 8 reports the results. The results show that firms with higher long-term leverage that borrow from banks expecting higher inflation tend to increase their capital expenditures in the following year, relative to firms with the same long-term leverage borrowing from banks with lower inflation expectations. The coefficient of interest, the first row, becomes statistically significant as additional controls are introduced. In our main specification (column 4), a firm with high leverage (i.e., long-term leverage over total assets equal to 0.5, or the 90^{th} percentile) borrowing from a bank expecting one percentage point higher inflation increases its capital expenditure by 8% percent ($0.16 \times 0.5 = 0.08$). To put the relevance of this channel for firms' investment decisions into perspective, high long-term leverage firms increase their capital expenditure relative more when borrowing from banks that expect higher inflation than when borrowing from banks that expect higher GDP growth, another important driver of lending decisions (Li and Ongena, 2025).

These results are align with a rich literature that documents heterogeneity in firms investment responses to (monetary policy) shocks depending on firm characteristics (Ottonello and Winberry, 2020; Jeenas, 2023). We find that firms with lower long-term leverage are less affected by this channel than firms with higher long-term leverage; for instance, a firm with an average long-term leverage level borrowing from a bank that expect 1% percent higher inflation increases its investment by 4% percent relative to another firm with the same level of long-term leverage borrowing from a bank expecting 1% percent lower inflation, compared to the 8% percent for a firm at the 90^{th} percentile of long-term leverage.

Consistent with the previous results, the interaction between short-term leverage and bank inflation forecasts is not statistically significant. This reinforces the result that only the component of debt easier to erode when inflation rise (long-term leverage) drives the effects in both credit allocation and firm investment.

6 Conclusion

This paper shows that banks expecting higher inflation tend to allocate more credit, and at lower rates, to firms with higher leverage, relative to banks with lower inflation expectations. These results are driven by long-term debt—the component of firm liabilities that is most easily eroded by inflation. In contrast, we find no significant differences in lending decisions across firms with varying levels of short-term debt, which is typically more flexible and offers fewer inflation-related advantages.

Our findings are consistent with the idea that banks internalize the inflation sensitivity of firms' capital structure. Firms with greater long term debt benefit more from inflation through a reduction in the real value of their debt, which lowers default risk and increases firm market value. Anticipating this, banks that expect higher inflation shift credit toward these firms.

Finally, we show that these credit reallocations translate into real effects: firms with higher long term debt that borrow from banks expecting higher inflation increase their capital expenditures in the following year, relative to otherwise similar firms borrowing from banks with lower inflation expectations.

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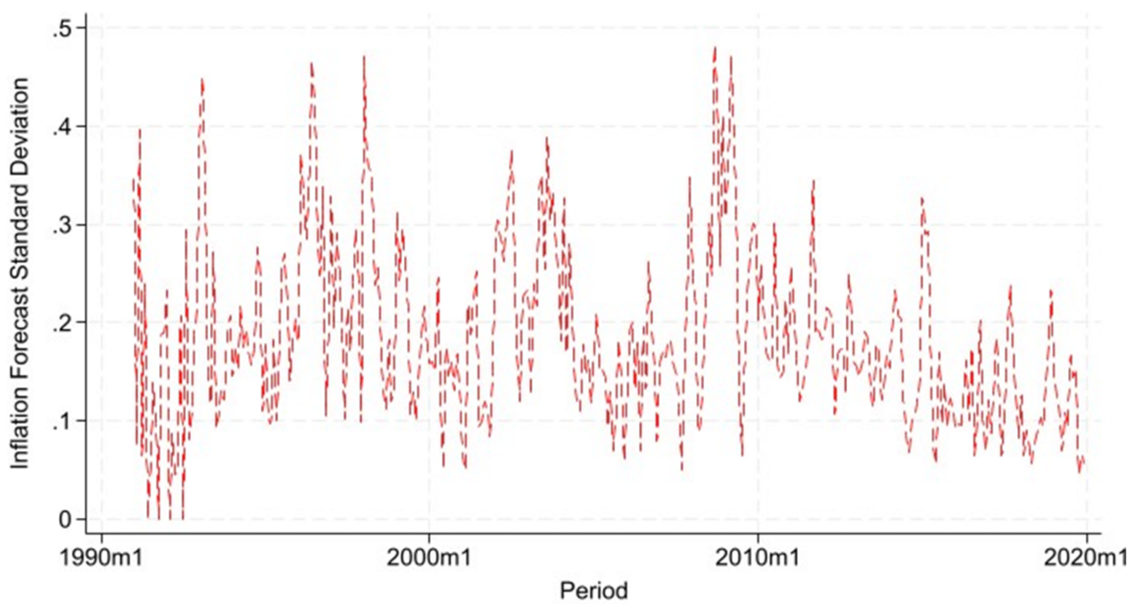
Figure 1: Inflation Expectations Dispersion



The figure plots the time-series of the standard deviation of the residuals from a regression of bank inflation forecasts on country×month fixed effects.

Table 1: Summary Statistics

Variable	Mean	Median	SD	p10	p25	p75	p90	Obs
Panel A: Consensus Economics								
Inflation Forecast	1.87	2.15	1.07	0.10	1.30	2.54	3.00	21142
GDP Forecast	2.36	2.35	0.89	1.27	1.80	3.00	3.50	21138
Long Interest Rate Forecast	3.95	4.67	2.13	1.05	1.74	5.60	6.40	19889
short Interest Rate Forecast	2.89	3.19	2.18	0.20	0.45	4.88	5.50	18655
Panel B: LPC DealScan								
Deal Amount (USD mil)	2009.86	393.90	6997.84	36.08	101.42	1447.41	4500.00	21142
Credit Line Amount (USD mil)	1859.16	375.00	5990.28	33.48	100.00	1350.00	4200.00	16935
Term Line Amount (USD mil)	1468.27	250.00	6221.80	25.00	73.86	900.00	2968.00	7497
Credit Line Spread (bps)	139.35	112.50	106.67	27.50	50.00	200.00	287.50	11477
Term Line Spread (bps)	239.63	218.75	153.37	75.00	125.00	300.00	425.00	4481
Maturity (Months)	44.97	42.00	37.05	12.00	18.00	60.00	72.00	20170
Maturity Credit (Months)	38.68	36.00	23.15	12.00	12.00	60.00	60.00	16092
Maturity Term (Months)	64.82	60.00	50.39	24.00	48.00	76.00	90.00	7230
Panel C: Compustat (Global and North America)								
Capital Expenditure	519.27	104.68	1188.70	7.00	25.52	426.23	1326.68	12998
Employment	22.67	6.50	41.61	0.65	1.95	22.19	62.00	20419
Long Leverage	0.26	0.23	0.19	0.03	0.12	0.35	0.50	21125
Short Leverage	0.07	0.04	0.09	0.00	0.01	0.09	0.17	21107
Profitability	0.11	0.10	0.07	0.04	0.07	0.15	0.20	21078
Tangibility	0.34	0.29	0.24	0.07	0.15	0.50	0.71	21068

This table reports summary statistics for all variables used in the empirical analysis. Panel A presents bank-level inflation and GDP growth forecasts from Consensus Economics. Panel B shows syndicated loan characteristics from LPC DealScan. Panel C reports firm-level variables from Compustat (Global and North America).

Table 2: Banks Inflation Forecast and Credit Line Amount

	(1) Log Amount	(2) Log Amount	(3) Log Amount	(4) Log Amount
$CPI^f \times$ Long Leverage	0.34***	0.28***	0.28***	0.31***
	(0.10)	(0.09)	(0.09)	(0.09)
CPI^f	-0.01	0.03	0.01	0.06
	(0.12)	(0.11)	(0.11)	(0.13)
Long Leverage	-0.97***	-0.84***	-0.72**	-0.74**
	(0.25)	(0.22)	(0.33)	(0.33)
GDP^f			0.21*	0.21*
			(0.11)	(0.11)
$GDP^f \times$ Long Leverage			-0.05	-0.05
			(0.10)	(0.10)
Firm FE	Yes	Yes	Yes	Yes
Country Time FE	Yes	Yes	Yes	Yes
Industry Time FE	No	Yes	Yes	Yes
Firm Controls	No	No	No	Yes
R^2	0.79	0.83	0.83	0.83
Observations	15281	14899	14893	14790

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is bank b lending to firm f, headquartered in country c and operating in industry k in month t. The dependent variable is the log of the credit line amount. The main coefficient of interest, reported in the first row, captures the interaction between firm long leverage (lagged one year) and bank inflation forecasts. All columns include firm and country-month fixed effects, and standard errors are clustered at the bank-country level. Column 3 additionally includes industry-by-year fixed effects, and the last column incorporates firm-level controls (such as profitability) and their interaction with bank inflation forecasts. Standard errors are clustered at the bank-country level. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 3: Banks Inflation Forecast, Spread, Credit Line

	(1) Spread	(2) Spread	(3) Spread	(4) Spread
$CPI^f \times$ Long Leverage	-28.80***	-29.18***	-30.25***	-35.72***
	(9.38)	(9.64)	(9.63)	(10.47)
CPI^f	4.49	-1.63	-0.51	-18.38*
	(8.32)	(8.44)	(8.01)	(11.10)
Long Leverage	135.75***	134.23***	110.74***	106.40***
	(23.30)	(24.45)	(37.25)	(39.98)
GDP^f			-6.35	-7.30
			(6.09)	(6.10)
$GDP^f \times$ Long Leverage			9.36	11.85
			(9.19)	(9.25)
Firm FE	Yes	Yes	Yes	Yes
Country Time FE	Yes	Yes	Yes	Yes
Industry Time FE	No	Yes	Yes	Yes
Firm Controls	No	No	No	Yes
R^2	0.74	0.80	0.80	0.81
Observations	9973	9487	9481	9398

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is bank b lending to firm f, headquartered in country c and operating in industry k in month t. The dependent variable is the credit line spread. The main coefficient of interest, reported in the first row, captures the interaction between firm long leverage (lagged one year) and bank inflation forecasts. All columns include firm and country-month fixed effects, and standard errors are clustered at the bank-country level. Column 3 additionally includes industry-by-year fixed effects, and the last column incorporates firm-level controls (such as profitability) and their interaction with bank inflation forecasts. Standard errors are clustered at the bank-country level. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 4: Banks Inflation Forecast and Credit Line Maturity

	(1) Maturity	(2) Maturity	(3) Maturity	(4) Maturity
$CPI^f \times$ Long Leverage	-0.31	-2.58*	-2.71*	-3.84**
	(1.77)	(1.53)	(1.49)	(1.84)
CPI^f	0.81	0.91	0.74	-0.30
	(1.08)	(1.10)	(1.09)	(1.23)
Long Leverage	3.67	7.45*	4.94	8.29
	(4.74)	(4.15)	(6.75)	(7.78)
GDP^f			2.54***	2.63***
			(0.98)	(1.00)
$GDP^f \times$ Long Leverage			1.07	0.85
			(1.80)	(1.84)
Firm FE	Yes	Yes	Yes	Yes
Country Time FE	Yes	Yes	Yes	Yes
Industry Time FE	No	Yes	Yes	Yes
Firm Controls	No	No	No	Yes
R^2	0.63	0.69	0.69	0.69
Observations	14379	13992	13988	13892

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is bank b lending to firm f, headquartered in country c and operating in industry k in month t. The dependent variable is the credit line maturity (in months). The main coefficient of interest, reported in the first row, captures the interaction between firm long leverage (lagged one year) and bank inflation forecasts. All columns include firm and country-month fixed effects, and standard errors are clustered at the bank-country level. Column 3 additionally includes industry-by-year fixed effects, and the last column incorporates firm-level controls (such as profitability) and their interaction with bank inflation forecasts. Standard errors are clustered at the bank-country level. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 5: Robustness to Interest Rates Forecast Measures

	(1) Log Amount	(2) Log Amount	(3) Spread	(4) Spread
$CPI^f \times$ Long Leverage	0.24**	0.27***	-30.05***	-34.09***
	(0.11)	(0.10)	(11.56)	(10.53)
CPI^f	-0.05	-0.03	11.08	2.94
	(0.09)	(0.08)	(7.18)	(6.95)
Long Leverage	-1.19***	-0.56*	95.39***	42.99
	(0.34)	(0.33)	(35.10)	(40.24)
$GDP^f \times$ Long Leverage	0.06	0.20	-2.24	-6.35
	(0.14)	(0.13)	(4.85)	(6.45)
GDP^f	0.11	-0.06	10.11	11.98
	(0.10)	(0.10)	(8.37)	(9.38)
3-$M^f \times$ Long Leverage	0.03		3.25	
	(0.03)		(4.47)	
3-M^f	0.06		-7.95	
	(0.13)		(5.74)	
$Y10^f \times$ Long Leverage		-0.01		12.69***
		(0.03)		(2.94)
$Y10^f$		0.02		-1.21
		(0.11)		(5.18)
Firm FE	Yes	Yes	Yes	Yes
Country-Time FE	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes
R^2	0.79	0.84	0.74	0.80
Observations	13,247	13,635	8,970	8,513

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is bank b lending to firm f, headquartered in country c and operating in industry k in month t. The dependent variable is the credit line amount in logs in the first two columns, and the spread in the last two. The main coefficient of interest, reported in the first row, captures the interaction between firm long leverage (lagged one year) and bank inflation forecasts. All columns include firm and country-month fixed effects, as well as industry-by-year fixed effects. Standard errors are clustered at the bank-country level. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 6: Robustness: Industry$\times$country$\times$month FE

	(1)	(2)
	Log Amount	Spread
CPI^f $\times$ Long Leverage	0.43***	-34.36***
	(0.10)	(12.49)
CPI^f	0.07	-9.01
	(0.13)	(12.15)
Long Leverage	-0.85**	96.24**
	(0.35)	(41.70)
GDP^f	0.18	-13.20**
	(0.11)	(6.07)
GDP^f $\times$ Long Leverage	-0.12	14.47
	(0.10)	(9.54)
Firm FE	Yes	Yes
Firm Controls	Yes	Yes
Industry Country Month FE	Yes	Yes
R^2	0.84	0.81
Observations	12,625	8,291

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is bank b lending to firm f, headquartered in country c and operating in industry k in month t. The dependent variable is the credit line amount in logs in the first column, and the spread in the last one. The main coefficient of interest, reported in the first row, captures the interaction between firm long leverage (lagged one year) and bank inflation forecasts. All columns include firm and industry month country fixed effects and firm-level controls (such as profitability) and their interaction with bank inflation forecasts.Standard errors are clustered at the bank-country level. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 7: Banks' Inflation Forecast, Credit Allocation and Pricing

Panel A: Log Credit Line Amount				
	(1)	(2)	(3)	(4)
	Log Amount	Log Amount	Log Amount	Log Amount
$CPI^f \times$ Long Leverage	0.33***	0.28***	0.28***	0.30***
	(0.10)	(0.09)	(0.09)	(0.10)
$CPI^f \times$ Short Leverage	-0.11	-0.08	-0.08	-0.05
	(0.12)	(0.13)	(0.13)	(0.14)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Country Time FE	Yes	Yes	Yes	Yes
Industry Time FE	No	Yes	Yes	Yes
Bank GDP Forecast	No	No	Yes	Yes
Firm Controls	No	No	No	Yes
R^2	0.79	0.83	0.83	0.83
Observations	15254	14871	14865	14738

Panel B: Credit Line Spread				
	Spread	Spread	Spread	Spread
$CPI^f \times$ Long Leverage	-31.39***	-30.84***	-31.76***	-37.09***
	(9.44)	(9.72)	(9.65)	(10.42)
$CPI^f \times$ Short Leverage	-25.08	-26.49	-32.60	-28.31
	(23.55)	(25.73)	(23.96)	(26.14)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Country Time FE	Yes	Yes	Yes	Yes
Industry Time FE	No	Yes	Yes	Yes
Bank GDP Forecast	No	No	Yes	Yes
Firm Controls	No	No	No	Yes
R^2	0.75	0.80	0.80	0.81
Observations	9953	9468	9462	9355

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is bank b lending to firm f, headquartered in country c and operating in industry k in month t. In Panel A (top panel) The dependent variable is the credit line amount in logs and in Panel B (bottom panel) the spread. All columns include firm and country-month fixed effects, and standard errors are clustered at the bank-country level. Column 3 additionally includes industry-by-year fixed effects, and the last column incorporates firm-level controls (such as profitability) and their interaction with bank inflation forecasts. Standard errors are clustered at the bank-country level. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 8: Banks Inflation Forecast, Short and Long Debt, and Firm Capital Expenditure 12 Months Ahead

	(1)	(2)	(3)	(4)
	$log\,Cap\;Exp_{y+1}$	$log\,Cap\;Exp_{y+1}$	$log\,Cap\;Exp_{y+1}$	$log\,Cap\;Exp_{y+1}$
$CPI^f \times$ Long Leverage	0.07	0.13*	0.14*	0.16**
	(0.07)	(0.08)	(0.08)	(0.08)
$CPI^f \times$ Short Leverage	0.10	0.22	0.24	0.20
	(0.19)	(0.22)	(0.21)	(0.21)
CPI^f	-0.01	-0.02	-0.03	-0.05
	(0.03)	(0.03)	(0.03)	(0.05)
Short Leverage	-0.88*	-1.06*	0.31	0.37
	(0.52)	(0.62)	(0.68)	(0.67)
Long Leverage	-0.58***	-0.73***	-0.56**	-0.54**
	(0.20)	(0.21)	(0.26)	(0.26)
$\log Cap_{t-1}$	0.41***	0.36***	0.36***	0.38***
	(0.02)	(0.03)	(0.03)	(0.03)
GDP^f			0.04*	0.06**
			(0.02)	(0.02)
$GDP^f \times$ Short Leverage			-0.51***	-0.50***
			(0.19)	(0.18)
$GDP^f \times$ Long Leverage			-0.07	-0.09
			(0.06)	(0.06)
Firm FE	Yes	Yes	Yes	Yes
Country Time FE	Yes	Yes	Yes	Yes
Industry Time FE	No	Yes	Yes	Yes
Firm Controls	No	No	No	Yes
R^2	0.94	0.96	0.96	0.96
Observations	8,391	7,919	7,917	7,890

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is bank b lending to firm f, headquartered in country c and operating in industry k in month t. The dependent variable is the log of the capital expenditure the following year. The main coefficient of interest, reported in the first row, captures the interaction between firm long leverage (lagged one year) and bank inflation forecasts, averaged at the firm level. All columns include firm and country-month fixed effects, and standard errors are clustered at the bank-country level. Column 3 additionally includes industry-by-year fixed effects, and the last column incorporates firm-level controls (such as profitability) and their interaction with bank inflation forecasts.Standard errors are clustered at the bank-country level. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Appendix

Appendix 1: Data sources and merging

We use three main sources of data: (i) syndicated loans from LPC Dealscan, (ii) firm balance sheets from Compustat, and (iii) bank forecasts from Consensus Economics. LPC Dealscan provides data on the loan characteristics such as Deal amount, facility margins, and spread. Notice that the first one is a variable at the deal level and the interest rate at the facility level. Compustat provides information on the firm financial condition. The main variable we use from this database is debt over assets. The sample consists of public firms, mainly in the US and Canada. Finally, Consensus Economics provides banks' and institutions' forecasts for different macro variables. The main variable of interest is the bank CPI forecast by the end of the following year.

To merge the three databases we take advantage of Chava and Roberts (2008) link file to combine LPC Dealscan with the Compustat, and we manually merge bank names between LPC Dealscan with Consensus Economics survey. Chava and Roberts (2008)'s link file combines LPC Dealscan $CompanyID$ (legacy ID) and Compustat ID ($gvkey$). LPC Dealscan $CompanyID$ (legacy ID) was the LPC Dealscan until 2021 when it was changed to the current LPC Dealscan $CompanyID$. WRDS-Reuters DealScan provides a link to connect the LPC Dealscan (legacy) with the current one.

Therefore, we need to proceed in two steps: (i) First, we combine the Chava and Roberts (2008) link with LPC Dealscan legacy $CompanyID$ (ii) and then connect this ID with the database with the current LPC Dealscan. To merge LPC Dealscan (legacy) facility with Chava and Roberts (2008) link through the FacilityID a facility unique indicator.[12] Then we connect this database with the current one through the "LoanConnector" provided by WRDS.[13] As a result, we obtain the current LPC Dealscan with a company ID ($gvkey$) which

[12] We obtain around 200,000 facilities with around 23,000 firms ($gvkey$) around the world. Fifty-five percent of the facilities (and a similar proportion of firms) are located in US and Canada. The time span of the sample is between April 1982 and January 2021. During this period, the median firm got eight facilities.

[13] The link between the new and old LPC Dealscan is not one-to-one. WRDS proposes

allows as to link this base with Compustat.

To do the merge with Compustat, we use the *gvkey* and the year the deal is active (LPC Dealscan) and the year the company reports its financial balance (Compustat). We use the year to maximize the number of observations, using the year and the quarter we loss around half of the observations. From Compustat we are going to use the average financial indicator over one year.[14]

To connect LPC Dealscan with Consensus Economics, we create our own link. We link each bank in Consensus Economics to the lender name in LPC Dealscan. We generate two type of links. In the first one, which is more restrictive, the name in Consensus needs to be part of the LPC Dealscan name. For instance, in the consensus Economics survey, we have a bank named "PNC Bank"; in LPC Dealscan we have a lender named "PNC Bank - Pittsburgh"; since "PNC Bank - Pittsburgh" contains "PNC Bank," we consider as the same bank in both databases. For the second criteria, it is enough if the lender's name in LPC Dealscan contains one word from the name in Consensus Economics, to connect both of them (in case the word does not have an actual meaning in the local language or English) for instance, in LPC Dealscan there is a lender called "PNC Capital Corp" under the second criteria we consider this bank as the same as"PNC Bank" in the first one we do not consider as part of "PNC Bank". To maximize the number of observations in the sample, we take the second criterion as the main link. Notice that LPC Dealscan provides information about the different participants in the deal. For each deal, we compute the average forecast for each variable. These are going to be considered the forecasts associated to the deal.

Finally, we collapse the database at the deal level. Therefore we construct a database with unique identification which is the deal. We generate descriptive variables for the two main types of facilities: term and credit.

to link both databases through tranche ID, deal Id, and tranche active date. See the following link https://wrds-www.wharton.upenn.edu/pages/support/manuals-and-overviews/thomson-reuters/wrds-reuters-dealscan/wrds-overview-on-dealscan-loanconnector

[14]We prepared the Compustat database before the merge making the yearly average and lagging the variables.

As a result of the merging process, we obtain a database at the deal-firm level. For each deal, we associated the average banks' expectation macro variables. The time span is between 1989 (when the consensus economics forecast survey started) and 2021 (until when we can use the Chava and Roberts (2008)'s link). The region with firms taking most deals is North America (mainly the US), especially for the data limitations of Compustat. We obtain 114,071 deals with deal amount different than zero, of which 33,829 for US and Canada.

Deal-Bank Forecast we have 50,425 deals with CPI forecast, 33,554 are for US and Canada.

Figure A1: CPI Forecast Histogram (US and Canada)

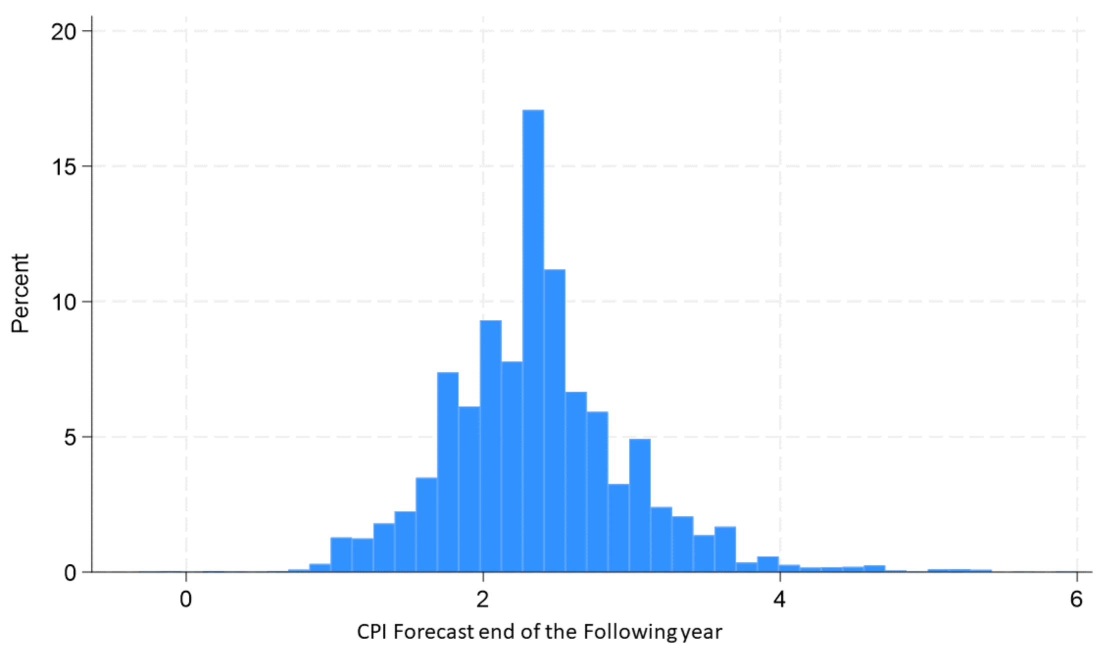


Figure A1 shows a relevant dispersion of CPI forecasts for US and Canada, going from 1% to 4%, in line with Figure 1 in the paper.

Number of Forecasts by Bank The final sample exhibits substantial heterogeneity across banks. Some institutions submitted more than five thousand CPI inflation forecasts, while others provided only a few observations. Table A1 presents the list of all banks that provide at least two hundred forecasts to Consensus Economics in the sample.

Table A1: Forecaster Banks with more than 200 total forecasts

Forecaster	N. of forecasts	Top target country	N. of top	Share (%)
Bank of America	6765	United States	6598	97.5
Bank of Tokyo-Mitsubishi UFJ	5991	Japan	5991	100.0
JP Morgan	5861	United States	5249	89.6
Mizuho Securities	3342	Japan	3342	100.0
NationsBank	3068	United States	3068	100.0
Wachovia Corp	1613	United States	1613	100.0
First Union Corp	1076	United States	1076	100.0
Smith Barney	1030	United States	1029	99.9
Credit Suisse	1030	United States	930	90.3
Wells Fargo	995	United States	995	100.0
Citigroup	929	United States	566	60.9
Barclays	899	United States	451	50.2
HSBC	887	United Kingdom	442	49.8
Northern Trust	856	United States	856	100.0
Goldman Sachs	761	United States	690	90.7
Morgan Stanley	588	United States	570	96.9
MUFG Bank	571	Japan	571	100.0
Merrill Lynch	521	United States	466	89.4
Continental Bank	512	United States	512	100.0
RBS	488	United Kingdom	482	98.8
BMO	400	Canada	390	97.5
BNP Paribas	399	France	266	66.7
Lehman Brothers	359	United States	353	98.3
Bankers Trust	314	United States	314	100.0
ING	268	United Kingdom	127	47.4
UBS	246	United States	133	54.1

Inflation and Interest Rate Forecasts Figures A2, A3 and A4 presents the average inflation, 3 month and 10 years interest-rate forecasts for the whole sample, US and Japan respectively. We observe there is a positive correlation between inflation and interest rate forecasts.

Figure A2

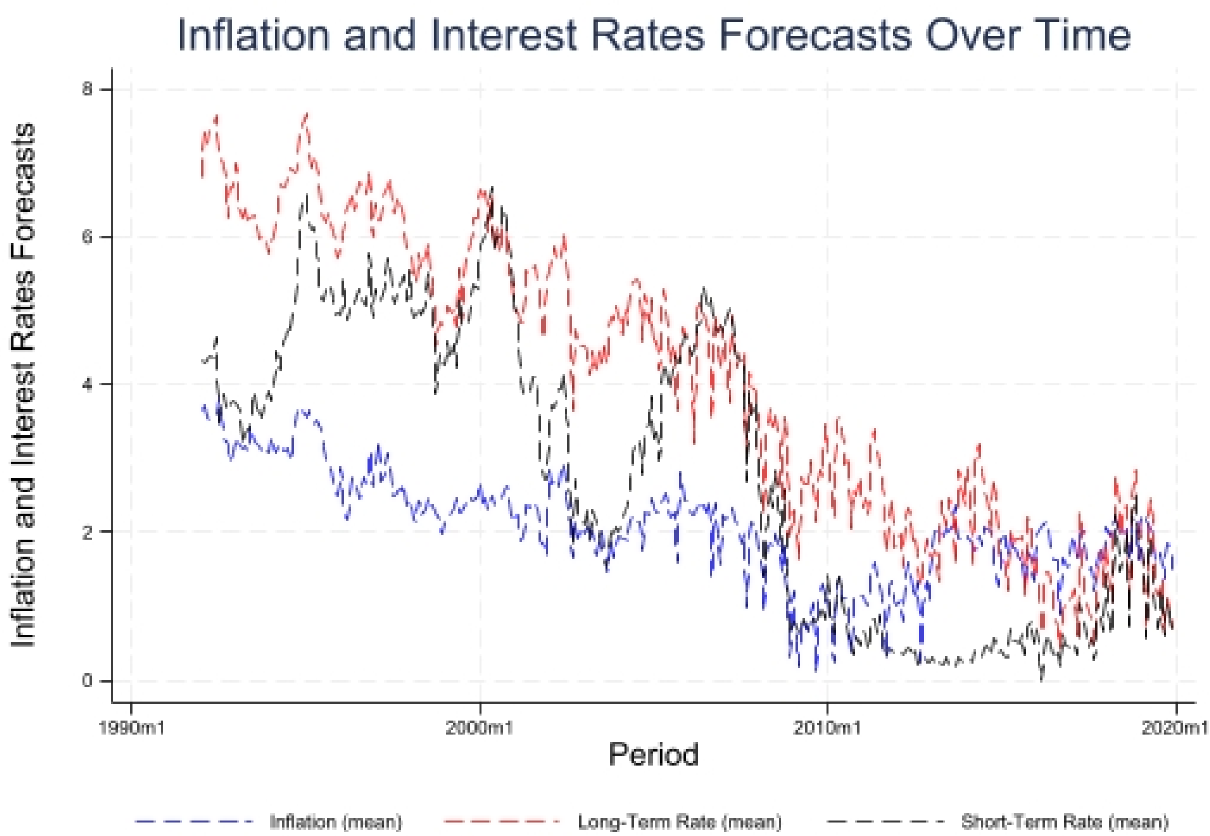

Inflation and Interest Rates Forecasts Over Time
Inflation and Interest Rates Forecasts
0
2
4
6
8
1990m1
2000m1
2010m1
2020m1
Period
Inflation (mean)
Long-Term Rate (mean)
Short-Term Rate (mean)

Figure A3

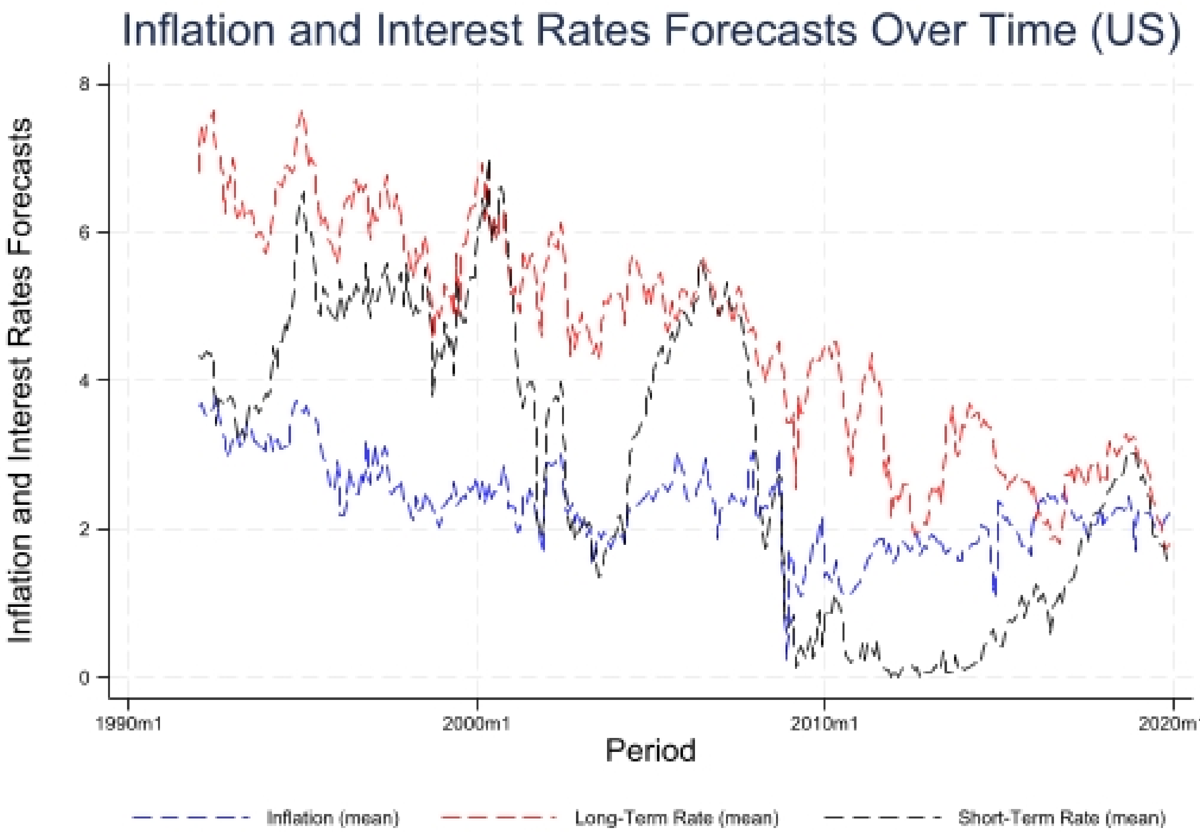
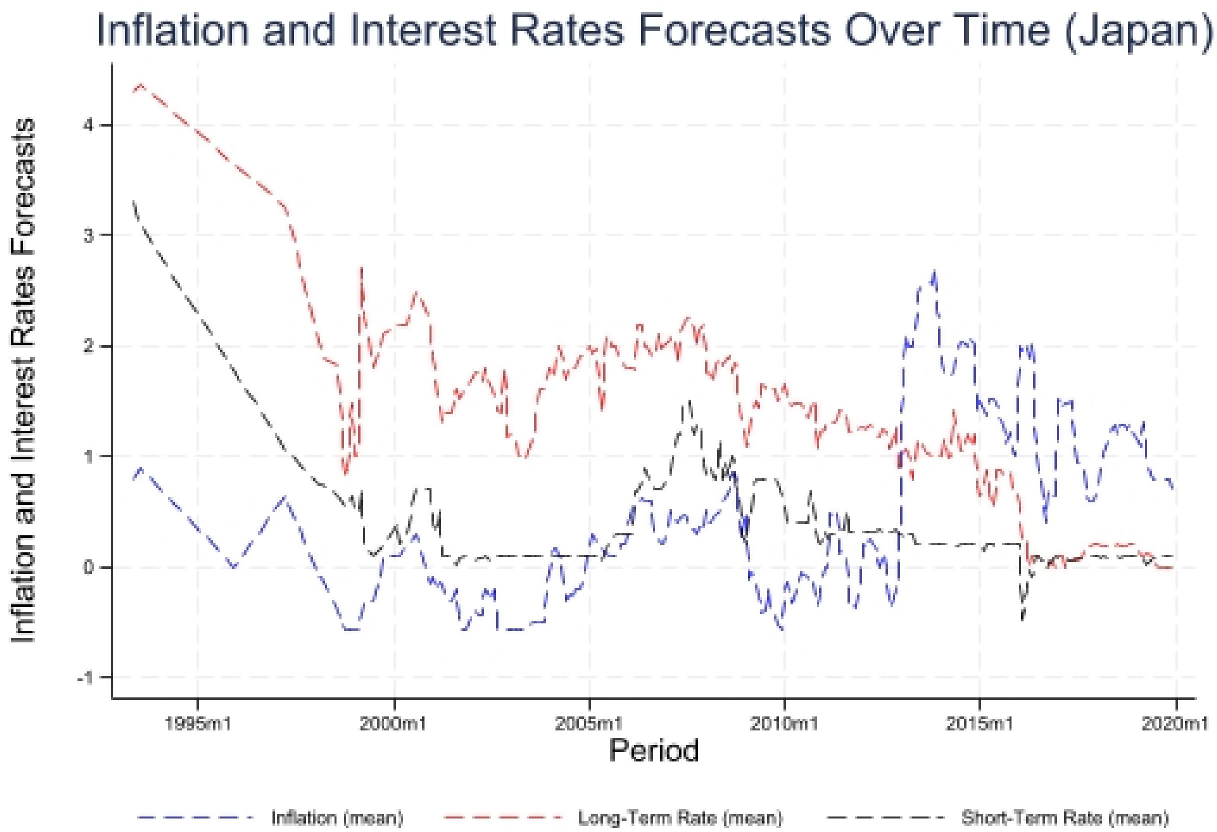

Inflation and Interest Rates Forecasts Over Time (US)
Inflation and Interest Rates Forecasts
0
2
4
6
8
1990m1
2000m1
2010m1
2020m1
Period
Inflation (mean)
Long-Term Rate (mean)
Short-Term Rate (mean)

Figure A4



Inflation and Interest Rates Forecasts Over Time (Japan)
Inflation and Interest Rates Forecasts
4
3
2
1
0
-1
1995m1
2000m1
2005m1
2010m1
2015m1
2020m1
Period
Inflation (mean)
Long-Term Rate (mean)
Short-Term Rate (mean)

Appendix 2: Baseline Robustness

This section presents several robustness checks to the baseline specification in Section 3. Importantly, all the results shown here are consistent with the main specification.

First, we show that the results of our main specification hold across different subsamples:

$$L_{b,f,c,k,t} = \beta_1 CPI^{f}_{b,c,t} + \beta_2 CPI^{f}_{b,c,t} \times Lev_{f,y-1} + \gamma GDP^{f}_{b,c,t} + \gamma_2 GDP^{f}_{b,c,t} \times Lev_{f,y-1} \tag{5}$$
$$+ \omega_{c,t} + \omega_f + \omega_{k,y} + \chi_{f,y-1} + \epsilon_{b,f,c,k,t},$$

As in Section 3, the coefficient of interest is again the interaction between bank inflation expectations, $CPI^{f}_{b,c,t}$, and lagged firm leverage, $Lev_{f,y-1}$.

We begin by dividing the sample into the two largest syndicated loan markets: the United States and Japan. These two markets are of particular interest because they have experienced different inflation dynamics. The U.S. has operated in a relatively low-inflation environment since the 1990s, while Japan has undergone a deflationary process with significant consequences for firm balance sheets. As shown in Tables A2 and A3, the main coefficient of interest is significant and has the expected sign in both cases when the dependent variable is the credit line log amount. Notably, in the case of Japan, the coefficient is even larger in the main specification (column 4), suggesting that this channel may be stronger in a deflationary environment.

Table A2: Banks Inflation Forecast and Credit Line Amount (US Sample)

	(1) Log Amount	(2) Log Amount	(3) Log Amount	(4) Log Amount
$CPI^f \times$ Long Leverage	0.44***	0.30**	0.30**	0.30*
	(0.13)	(0.14)	(0.14)	(0.15)
CPI^f	-0.04	0.04	0.02	0.04
	(0.14)	(0.13)	(0.12)	(0.10)
Long Leverage	-1.24***	-0.90**	-0.76	-0.76
	(0.34)	(0.36)	(0.50)	(0.52)
GDP^f			0.26*	0.25***
			(0.14)	(0.07)
$GDP^f \times$ Long Leverage			-0.05	-0.02
			(0.12)	(0.12)
Firm FE	Yes	Yes	Yes	Yes
Country Time FE	Yes	Yes	Yes	Yes
Industry Time FE	No	Yes	Yes	Yes
Firm Controls	No	No	No	Yes
R^2	0.74	0.79	0.79	0.79
Observations	10131	9684	9678	9572

Note: Standard errors in parentheses, clustered at the firm-bank level.

Table A3: Banks Inflation Forecast and Credit Line Amount (JP Sample)

	(1) Log Amount	(2) Log Amount	(3) Log Amount	(4) Log Amount
$CPI^f \times$ Long Leverage	0.08	0.41***	0.35***	0.41***
	(0.09)	(0.11)	(0.10)	(0.16)
CPI^f	0.03	0.08	0.10	0.12
	(0.14)	(0.16)	(0.16)	(0.10)
Long Leverage	0.17	-0.43	0.32	0.32
	(0.44)	(0.37)	(0.56)	(0.44)
GDP^f			0.08	0.08
			(0.14)	(0.07)
$GDP^f \times$ Long Leverage			-0.43**	-0.43**
			(0.20)	(0.17)
Firm FE	Yes	Yes	Yes	Yes
Country Time FE	Yes	Yes	Yes	Yes
Industry Time FE	No	Yes	Yes	Yes
Firm Controls	No	No	No	Yes
R^2	0.88	0.92	0.92	0.92
Observations	3514	3239	3239	3238

Note: Standard errors in parentheses, clustered at the firm-bank level.

Table A4 presents the results of the baseline specification using the spread as the dependent variable, restricted to the U.S. sample. The results are nearly identical to those obtained for the full sample.

Table A4: Banks Inflation Forecast, Spread, Credit Line (US)

	(1) Spread	(2) Spread	(3) Spread	(4) Spread
$CPI^f \times$ Long Leverage	-31.88***	-31.59***	-32.56***	-35.88***
	(9.58)	(9.43)	(9.43)	(10.32)
CPI^f	5.95	0.32	1.34	-18.37
	(8.12)	(8.10)	(7.76)	(11.20)
Long Leverage	145.21***	140.75***	119.41***	105.58***
	(23.95)	(24.23)	(37.91)	(40.84)
GDP^f			-5.84	-6.64
			(5.76)	(5.81)
$GDP^f \times$ Long Leverage			8.44	12.32
			(9.40)	(9.52)
Firm FE	Yes	Yes	Yes	Yes
Country Time FE	Yes	Yes	Yes	Yes
Industry Time FE	No	Yes	Yes	Yes
Firm Controls	No	No	No	Yes
R^2	0.74	0.80	0.80	0.80
Observations	9147	8678	8672	8601

Note: Standard errors in parentheses, clustered at the firm-bank level.

We can also rule out that the 2007 financial crisis drives our results, by re-estimating the baseline specification using only the pre-crisis subsample. Tables A5 shows that the results for this subsample are similar to those obtained with the full sample.

Table A5: Banks' Inflation Forecast and Credit Line Spread Pre-Crisis

	(1) Spread	(2) Spread	(3) Spread	(4) Spread
$CPI^f \times$ Long Leverage	-23.17**	-31.20***	-31.89***	-30.17**
	(11.31)	(11.01)	(11.07)	(12.03)
CPI^f	7.17	6.24	6.70	-13.00
	(8.57)	(7.65)	(7.52)	(10.91)
Long Leverage	114.83***	133.08***	110.34***	80.89*
	(31.24)	(31.70)	(40.33)	(41.47)
GDP^f			-1.07	-2.19
			(5.81)	(5.77)
$GDP^f \times$ Leverage			8.59	12.36
			(9.01)	(8.74)
Firm FE	Yes	Yes	Yes	Yes
Country-Time FE	Yes	Yes	Yes	Yes
Industry-Time FE	No	Yes	Yes	Yes
Firm Controls	No	No	No	Yes
R^2	0.75	0.80	0.80	0.80
Observations	7681	7463	7457	7384

Note: Standard errors in parentheses, clustered at the firm-bank level.

As additional robustness test, we run our main specification using the total deal amount rather than only the credit line component. As previously mentioned, this specification combines different facility types, such as credit lines and term loans, which differ in nature. Still, we want to assess whether the overall deal amount shows a similar effect. Table A6 confirms that this is indeed the case.

Table A6: Banks Inflation Forecast and Deal Amount

	(1) Log Deal Amount	(2) Log Deal Amount	(3) Log Deal Amount	(4) Log Deal Amount
$CPI^f \times$ Long Leverage	0.25***	0.20***	0.20***	0.22***
	(0.09)	(0.07)	(0.08)	(0.08)
CPI^f	-0.03	0.01	0.00	0.02
	(0.09)	(0.08)	(0.08)	(0.09)
Long Leverage	-0.59***	-0.46**	-0.39	-0.36
	(0.23)	(0.19)	(0.28)	(0.28)
GDP^f			0.06	0.07
			(0.13)	(0.13)
$GDP^f \times$ Leverage			-0.03	-0.04
			(0.10)	(0.10)
Firm FE	Yes	Yes	Yes	Yes
Country Time FE	Yes	Yes	Yes	Yes
Industry Time FE	No	Yes	Yes	Yes
Firm Controls	No	No	No	Yes
R^2	0.77	0.80	0.80	0.80
Observations	19634	19313	19307	19168

Note: Standard errors in parentheses, clustered at the firm-bank level.

Tables A7 and A8 show that considering the forecasts of only lead arrangers we have similar results as in the main specification.

Table A7: Banks Inflation Forecast and Loans' Amount (Only Lead Arrangers)

	(1) Log Amount	(2) Log Amount	(3) Log Amount	(4) Log Amount
$CPI^f \times$ Long Leverage	0.30**	0.26**	0.26**	0.24**
	(0.12)	(0.11)	(0.11)	(0.12)
CPI^f	-0.00	0.05	0.05	0.04
	(0.09)	(0.09)	(0.09)	(0.10)
Long Leverage	-0.80***	-0.75**	-0.26	-0.21
	(0.30)	(0.29)	(0.37)	(0.39)
GDP^f			0.12	0.12
			(0.09)	(0.09)
$GDP^f \times$ Leverage			-0.19**	-0.18*
			(0.09)	(0.10)
Firm FE	Yes	Yes	Yes	Yes
Country Time FE	Yes	Yes	Yes	Yes
Industry Time FE	No	Yes	Yes	Yes
Firm Controls	No	No	No	Yes
R^2	0.81	0.85	0.85	0.85
Observations	11315	10861	10857	10793

Note:Standard errors in parentheses, clustered at the firm-bank level.

Table A8: Banks Inflation Forecast, Spread, Credit Line (Only Lead Arrangers)

	(1) Spread	(2) Spread	(3) Spread	(4) Spread
$CPI^f \times$ Long Leverage	-24.22**	-19.43*	-20.32*	-22.98**
	(10.11)	(10.73)	(10.78)	(11.11)
CPI^f	10.75	3.84	4.95	-8.02
	(6.96)	(7.80)	(7.73)	(10.08)
Long Leverage	125.41***	113.86***	85.98**	75.26**
	(25.85)	(29.54)	(35.44)	(36.09)
GDP^f			-7.89	-8.03
			(5.06)	(5.13)
$GDP^f \times$ Leverage			10.87	14.69
			(10.04)	(10.25)
Firm FE	Yes	Yes	Yes	Yes
Country Time FE	Yes	Yes	Yes	Yes
Industry Time FE	No	Yes	Yes	Yes
Controls Firm	No	No	No	Yes
R^2	0.76	0.84	0.84	0.84
Observations	7176	6627	6623	6570

Note:Standard errors in parentheses, clustered at the firm-bank level.

Table A9: Banks Inflation Forecast and Term Line Maturity

	(1) Maturity	(2) Maturity	(3) Maturity	(4) Maturity
$CPI^f \times$ Long Leverage	-5.89*	-2.20	-2.12	-2.54
	(3.31)	(7.31)	(6.79)	(7.99)
CPI^f	1.27	-3.22	-3.25	-1.34
	(3.08)	(5.07)	(4.94)	(5.41)
Long Leverage	24.75***	22.10	20.99	18.04
	(8.66)	(19.87)	(36.04)	(36.97)
GDP^f			-0.67	-0.93
			(3.07)	(2.96)
$GDP^f \times$ Long Leverage			0.58	1.85
			(8.28)	(7.78)
Firm FE	Yes	Yes	Yes	Yes
Country Time FE	Yes	Yes	Yes	Yes
Industry Time FE	No	Yes	Yes	Yes
Firm Controls	No	No	No	Yes
R^2	0.44	0.63	0.63	0.64
Observations	5219	4581	4580	4547

Note: Standard errors in parentheses, clustered at the firm-bank level.