# Banks' Inflation Expectations and Credit Allocation: the Fisher Effect

Filippo De Marco* Diego Friedheim†

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**Abstract**

This paper investigates how lenders' inflation expectations shape credit allocation. Banks expecting higher inflation reallocate credit toward leveraged firms, which benefit from a reduction in the real burden of nominal debt. To test this hypothesis, we combine individual bank-level macroeconomic inflation forecasts for developed economies with syndicated loan data spanning 1991–2021. We show that banks expecting a one percentage point higher inflation rate over the subsequent year extend 18% more credit at spreads that are 10% lower to highly leveraged firms, relative to banks with lower inflation expectations. Importantly, these effects are concentrated among firms with high long-term leverage, rather than short-term leverage, whose real value is less affected by inflation. Because the additional bank credit is cheaper, firms change their capital structure, substituting away from bond financing and into floating-rate credit lines. As a result, firms deleverage overall, lowering their exposure to inflation risk. Our findings suggest that lenders' inflation expectations play an important role in credit allocation and have implications for financial stability by affecting firm leverage.

Keywords: Inflation expectations, credit supply, Fisher effect, leverage

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*Bocconi University, Baffi, IGIER and CEPR. filippo.demarco@unibocconi.it

†Di Tella University diego.friedheim@utdt.edu

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# 1 Introduction

Inflation erodes the real value of liabilities: as inflation rises, the real burden of debt falls. This phenomenon is commonly referred to as the Fisher effect (Fisher, 1933).[1] Higher inflation therefore 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 there is some evidence on how inflation can affect the real economy via its effects on bank balance sheets (e.g. Agarwal and Baron, 2024), we know little about how lenders' expectations affect credit allocation.

This paper investigates this novel credit-Fisher hypothesis by analyzing how lenders' inflation expectations influence their credit allocation across firms with different ex-ante leverage. To do this, 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. Exploiting dispersion across banks in inflation forecasts for the same country and period, we test whether higher inflation expectations translate into larger loans at lower rates to leveraged firms.

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. Using the forecasters' names reported in Consensus Economics and lenders' names in LPC DealScan, we create a match 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,

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

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 18,000 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, 18% more credit in the form of credit lines and charges 10% 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. These magnitudes are significant, and correspond to about 45% and 30% of the "financing gap" between highly and lowly leveraged firms in loan amounts and interest rate spreads, respectively. 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.

Beyond banks' credit supply, we show that banks' inflation expectations affect firms' capital structure choices. The additional credit extended by banks expecting higher inflation takes the form of larger and cheaper credit lines, which are particularly valuable for managing liquidity needs. Because credit lines can be drawn on demand and are not recorded as debt until they are used, securing a more favorable line reduces firms' reliance on other forms of external financing. We find that highly leveraged firms borrowing from banks with higher inflation expectations reduce their overall leverage in the year following the loan, despite receiving more bank credit. This happens because the additional bank credit becomes cheaper, closing the gap with bond funding (Schwert, 2020). The decline in leverage is economically meaningful: firms at the top decile of the long-term leverage distribution reduce their total leverage by about 2 percentage points (about 4% of the average) when borrowing from a bank whose inflation forecast is one percentage point higher.

This reduction in leverage is driven by substitution away from bond financing. Using bond issuance data for North American firms, we show that highly leveraged borrowers that receive a loan from a bank expecting higher inflation issue smaller amounts of long-term bonds in the subsequent years. The decline in bond issuance more than offsets the increase in bank borrowing, leading to a net reduction in leverage overall. Moreover, because credit lines typically carry floating interest rates (Ippolito et al., 2018), the resulting increase in bank borrowing shifts firms' debt composition toward instruments whose real value is less sensitive to inflation than long-term fixed-rate bonds. As a result, firms lower their exposure to inflation risk. These findings highlight a novel channel through which lenders' inflation expectations can influence firm balance sheets and financial stability.

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. 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.

We address several potential concerns regarding the interpretation of our results. One concern is that banks' inflation forecasts may be correlated with other macroeconomic expectations, such as forecasts of future monetary policy rates, long-term interest rates, or GDP growth, which could jointly influence both inflation expectations and lending decisions (Li and Ongena, 2025). Consensus Economics provides forecasts for a wide range of macroeconomic and financial variables, including short-term (3-month) and long-term (10-year) interest rates, as well as GDP growth, allowing us to assess this possibility directly. First, we find limited correlation between inflation forecasts and these alternative forecasts. As expected, the highest correlation is between inflation and short-term interest rate forecasts, with a coefficient of only 0.36. Second, we include these additional forecasts as controls in our regressions, along with their interactions with firms' long-term leverage. The coefficient of interest remains statistically significant and of similar magnitude. Finally, we show that our results are robust to the inclusion of additional controls, to alternative geographic subsamples, and to different sample periods.

This paper contributes to several 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; Friedheim, 2025). In the context of credit markets, 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). Ma et al. (2021) show that US banks with pessimistic house price expectations lend less to local firms and D'Acunto et al. (2024) provide experimental evidence from China that macroeconomic expectations 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 US inflation in the 1970s to show that unexpected increases in inflation reduce bank lending (see also recent evidence in Ranaldi (2025)) 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.

[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.

# 2 Data and Stylized Facts about Expectations

## 2.1 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. This dataset has been widely used in the literature to study a range of international finance and macroeconomic questions (De Marco et al., 2022; Kalemli-Ozcan and Varela, 2021; Friedheim, 2025). 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 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

[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.

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.

We match bank-level 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 and location 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 lead arranger forecast, in case there is more than one lead arranger in both Conensus and LPC Dealscan we consider the simple average of each lead arranger forecast.

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

[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 $margin$.

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 only consider banks whose role in deal is classified as "lead arranger". 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 additional funding (Roberts, 2015).

The resulting dataset contains over 18,000 deals between 1991 and 2021.[6] 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 around 14,500 facilities, and term loans the second most common with around 6,800 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.

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

## 2.2 Bank Forecasts: Stylized facts

A key feature for our purposes is the substantial dispersion in banks' one-year ahead inflation forecasts both across banks and over time. Figure 1 plots median, $10^{th}$ and $90^{th}$ percentile of bank inflation forecasts for the United State Economy (which represents over a half of the observation in our sample) for our sample of banks. The figure shows that there are two inflationary regimes during the sample period: a downward trend in the 1990s, which then flattens out during the 2000s, with a deflationary spike during the global financial crisis in 2008. While the time trend is insightful, we do not exploit such aggregate variation over time in inflation forecasts. Most importantly for our purposes there is a substantial forecast range between 1-2 percentage points throughout the sample period, similar to the level of the median forecasts.

Specifically, we exploit variation across banks forecasting inflation for the same country in the same month. Figure 2 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 related consideration is how strongly correlated banks' inflation forecasts are with other macro forecasts (GDP, short rate, and long rate). If these forecasts were highly correlated, inflation forecasts would simply proxy for these variables. Panel A of Table 2 reports cross-forecast correlations after absorbing country and month fixed effects (that is, among banks forecasting the same country in the same month). Correlations are generally low: for example, the coefficient of correlation between inflation and GDP forecasts is about 0.10 and it is higher, but still modest, with 3-month interest rate forecasts (0.36). We nevertheless include all macro forecasts as controls in our estimations.

Another important feature of the forecast data, with implications for our empirical design, is that the ranking of banks by inflation expectations varies over time. This means that banks expecting higher inflation are not persistent over time and there is substantial reshuffling. To illustrate this, we sort bank–year observations for the United State (the country with most observations and a balanced panel) into quintiles based on the next–year inflation forecast. Panel B of Table 2 reports the resulting transition matrix. The diagonal entries are well below one, indicating that a bank in a given quintile in period $t$ has a substantial probability of moving to a different quintile in period $t+1$. For example, banks in the upper quintile of inflation forecasts have only a 56% probability of remaining in the same quintile in the next month, and there is substantial movement from the second and third into the top quintile.

# 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.[7] Our baseline specification is:

$$\begin{aligned} L_{b,f,c,k,t} = {} & \beta_1 \, \mathbb{E}\Big(CPI^{y+1}_{b,c,t}\Big) \times Lev_{f,y-1} + \beta_2 \, \mathbb{E}\Big(CPI^{y+1}_{b,c,t}\Big) + \beta_3 \, Lev_{f,y-1} \\ & + \sum_j \gamma_j \, \mathbb{E}\Big(X^{y+1}_{b,c,t}(j)\Big) + \sum_j \alpha_j \, \mathbb{E}\Big(X^{y+1}_{b,c,t}(j)\Big) \times Lev_{f,y-1} \\ & + \chi_{f,y-1,b} + \omega_{c,t} + \omega_f + \omega_{k,y} + \epsilon_{b,f,c,k,t} \, , \end{aligned} \tag{1}$$

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 $f$, located in country $c$ and operating in sector $k$, in month $t$. The variable $\mathbb{E}(CPI^{y+1}_{b,c,t})$ is

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

the bank-level forecast for the end-of-next-year inflation (i.e., annual CPI growth between current end-of-year $y$ and end-of-next-year $y+1$) for country $c$, produced by bank $b$ at month $t$. The term $Lev_{f,y-1}$ denotes firm $f$'s long-term leverage ratio in the previous year $(y-1)$. $\mathbb{E}(X^{y+1}_{b,c,t}(j))$ denotes the bank's other one-year-ahead forecast of macroeconomic variables. In the baseline, $X(j)$ corresponds to GDP growth for next year (i.e., the expected growth rate for the following calendar year). $\chi_{f,y-1,b}$ includes firm-level controls, such as lagged profitability and tangibility and their interaction with bank inflation forecasts. $\omega_f$ denote firm fixed effects, $\omega_{c,t}$ are country month fixed effects, and $\omega_{k,y}$ represent two digit (SIC Code) industry-year fixed effects.

Given the presence of country month fixed effects, $\omega_{c,t}$, the coefficient on $\mathbb{E}(CPI^{y+1}_{b,c,t})$ captures the bank-specific variation from the mean forecast for the country vis-à-vis other banks. Figure 2 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.

The main coefficient of interest is $\beta_1$, which captures the effect of the interaction between the bank's inflation forecast, $\mathbb{E}(CPI^{y+1}_{b,c,t})$, and the firm's lagged long-term leverage, $Lev_{f,y-1}$. 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 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. We also include firm fixed effects to absorb time-invariant unobserved firm characteristics, including their preference for high leverage, country month fixed effects which control for the specific shocks each country suffer each month, and two digit (SIC Code) industry-year fixed effects, to control for industry-time varying shocks. Finally, we normalize $Lev_{f,y-1}$ by its sample 90th-percentile value, so that a unit corresponds to a firm at the $90^{th}$ percentile.

Table 3 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 18% 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. 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 45% of this financing gap (0.18/0.40=0.45).

Table 4 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 14.7 basis points lower to a high leverage (i.e., $90^{th}$ percentile) firm than a bank expecting inflation to be 1 percentage point lower. This effect represent 10% 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 30% of this financing gap ($14.69/47.6 = 0.31$).

## 3.1 Robustness

The results from Table 3 and Table 4 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.[8] We therfore augment our baseline specification from Equation (1) with a bank-level interest rate forecast variable: the three-month interest rate forecast, $\mathbb{E}(3M^{y+1})$, or the ten-year sovereign bond yield forecast, $\mathbb{E}(Y10^{y+1})$. These forecasts enter the regression both directly and interacted with the firm's lagged long-term leverage.[9]

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

[9] We do not include these forecast variable in our baseline specification as they are not as well populated as GDP or CPI forecasts for all bank-country pairs.

Table 5 presents the results. 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, $\mathbb{E}(3M^{y+1})$, while Columns 2 and 4 include the ten-year sovereign bond yield, $\mathbb{E}(Y10^{y+1})$. 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 Table 3 and Table 4. 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 for this somewhat puzzling result 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]

In Appendix 2 we also address another potential concern, namely the selection on the firm side: firms borrowing from banks with higher inflation expectations may differ systematically from those borrowing from banks with lower expectations. To address this, we restrict the sample to firms that obtain more than one syndicated loan within a given year and include firm-year fixed effects. This controls for all unobservable characteristics at the firm-year level. The effect we find is even stronger for this subsample. The results are also robust to introduce one digit industry times country times month fixed effects. Moreover, Appendix 2 shows that our baseline findings also hold at the deal level and are robust across time periods (before and after the 2007 financial crisis) and for the US subsample. The results are also robust to including amended deals in the sample, and there

[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 around 0.3. Figures A2, A3 and A4 in Appendix 1 show the correlation over time between these forecasts.

are similar results for other interest rates in the credit line facility.

### 3.2 Short vs. long-term leverage

As previously discussed, there is a crucial distinction between long- and short-term corporate debt. It is well known 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 (Gomes et al., 2016). 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,

Table 6 reports the results. 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.

# 4 De-leveraging

Firms with higher long term leverage obtain larger loans at lower spreads from banks that expect higher inflation. In particular, they receive larger and cheaper credit lines, which are especially useful for managing liquidity needs (Acharya et al., 2021; Cooperman et al., 2025). Since a credit lines can be drawn upon on demand, securing a larger and cheaper one reduces the need to issue other debt and might help the firm to reduce its total leverage.[11] Therefore we hypothesize that, after securing a larger credit line, firms rebalance their liabilities by reducing other funding sources, such as long-term bond issuance.

To test this hypothesis we first analyze if the ratio of total leverage to total assets in the period after a highly leveraged firm obtains a credit line is reduced for those which obtain the loan from a bank expecting higher inflation. To this end, we run the following specification:

$$\begin{aligned} TotLev_{f,t+1} = {} & \beta_1 \mathbb{E}(CPI_{b,c,t}^{y+1}) \times Lev_{f,y-1} + \beta_2 \mathbb{E}(CPI_{b,c,t}^{y+1}) + \beta_3 Lev_{f,y-1} \\ & + \sum_j \gamma_j \, \mathbb{E}\Big(X_{b,c,t}^{y+1}(j)\Big) + \sum_j \alpha_j \, \mathbb{E}\Big(X_{b,c,t}^{y+1}(j)\Big) \times Lev_{f,y-1} \\ & + \Theta_{f,y-1,b} + \omega_{c,y} + \omega_f + \omega_{k,y} + \chi_{f,y-1,b} + \epsilon_{b,f,c,y}, \end{aligned} \tag{2}$$

where the dependent variable is the ratio of total (i.e., long and short) term leverage over total assets. We also include interactions of bank inflation ($\mathbb{E}(CPI_{b,c,t}^{y+1})$) and GDP forecasts ($\mathbb{E}(X_{b,c,t}^{y+1}(j))$) with both long and short leverage. Where $\Theta_{f,y-1,b}$ represents the short leverage and it interaction with both bank forecasts. The coefficient of interest, $\beta_1$, captures the interaction between firm leverage and bank inflation expectations.

Table 7 shows that a firm at the $90^{th}$ percentile of long leverage in the year prior to the loan reduces its total leverage by 2 percentage points if it borrows from a bank

[11] Notice that the credit line is not computed as a debt until the firm drawn on it.

whose inflation forecast is 1 percentage point higher, relative to an otherwise similar firm borrowing from a bank with a 1 percentage point lower forecast. This corresponds to a 4% decline for a firm with 90% leverage. The coefficient of interest is statistically significant and remarkably stable across specifications.

To examine whether firms substitute away from other funding sources, we study new corporate bond issuance. For North American firms, we merge bond issuance records from Mergent Fisd with our database, yielding a dataset that combines balance sheet information and bond issuance with syndicated loan characteristics and banks' macroeconomic forecasts. Mergent FISD contains information on the corporate primary bond market issuance including the amount issued, maturity and the yield at issuance. We are able to find 387 firms (using the issuer CUSIP as the firm identifier) that issue over 1,945 bonds after obtaining a syndicated loan. We then test whether firms reduce bond issuance in the two years after receiving a deal from a bank expecting higher inflation. Among firms that issue a bond after receiving a deal, half do so within the first two years.[12]

We estimate a specification analogous to the baseline, with the dependent variable equal to the log of the total amount of bonds issued by firm $f$ between the month of the loan deal ($t$) and two years after, $t+2$. We include firm fixed effects and country$\times$year fixed effects to reflect the different frequency of the data. We also include the interaction of GDP forecasts with long leverage and, as an additional control, the interaction of short leverage with the bank's inflation forecast, $\Theta_{f,y-1,b}$.

$$\begin{aligned} log(Bond) = {} & \beta_1 \mathbb{E}(CPI^{y+1}_{b,c,t}) \times Lev_{f,y-1} + \beta_2 \mathbb{E}(CPI^{y+1}_{b,c,t}) + \beta_3 Lev_{f,y-1} \\ & + \sum_j \gamma_j \, \mathbb{E}\Big(X^{y+1}_{b,c,t}(j)\Big) + \sum_j \alpha_j \, \mathbb{E}\Big(X^{y+1}_{b,c,t}(j)\Big) \times Lev_{f,y-1} + \Theta_{f,y-1,b} + \omega_{c,y} + \omega_f + \epsilon_{b,f,c,t}. \end{aligned} \tag{3}$$

Table 8 reports the results. We find that high leverage firms that receive a loan from a

[12]In our sample, within two years after receiving a deal, 195 firms issue at least one bond, for a total of 902 bond issues.

bank expecting higher inflation issue bonds in smaller amounts. For this subsample, the total amount offered declines. These results suggest that, after obtaining a loan from a bank with higher inflation expectations, firms substitute away from bond financing, which contributes to lower leverage in the following year.

## 5 Conclusions

This paper's main result is that banks' inflation expectations affect who receives credit and on what terms, depending on borrowers' liability structure. Banks expecting higher inflation expand credit supply and lower spreads specifically for firms with high long-term leverage, which is the component of debt whose real value is most readily eroded by inflation. This pattern is consistent with banks internalizing the Fisher effect when making credit supply decisions: expected inflation improves the repayment prospects of firms with inflation-exposed nominal liabilities, and banks with higher inflation expectations reallocate lending toward these borrowers.

Importantly, this credit reallocation does not mechanically increase leverage. Because the additional bank credit is cheaper and largely provided through credit lines, which have a floating-rate, highly leveraged firms substitute away from long-term bond financing. We find that firms borrowing from banks with higher inflation expectations reduce subsequent long-term bond issuance and, on net, deleverage. This implies that lender beliefs can influence not only credit allocation but also firms' capital structure and exposure to inflation risk.

These findings have two policy implications. First, they point to an expectations-driven channel through which inflation expectations shape the transmission of monetary policy to corporate credit. Even holding aggregate inflation constant, dispersion in inflation expectations across banks can generate heterogeneous credit supply conditions across firms and shift the composition of borrowing between bank and bond markets. Second, the results suggest that inflation expectations can have financial stability consequences through their effect on leverage dynamics. To the extent that higher inflation expectations induce banks to lend more cheaply to firms whose nominal debt burden is most sensitive to inflation, credit markets may contribute to stabilizing corporate leverage during inflationary episodes. At the same time, because this mechanism depends on lenders' expectations, abrupt changes in inflation forecasts could lead to rapid shifts in credit allocation, making the monitoring of inflation expectations in the banking sector relevant for macroprudential policy.

# References

**Acharya, Viral, Heitor Almeida, Filippo Ippolito, and Ander Perez**, "Credit lines as monitored liquidity insurance: Theory and evidence," *Journal of Financial Economics*, 2014, *112* (3), 287–319.

**Acharya, Viral V, Heitor Almeida, Filippo Ippolito, and Ander Perez-Orive**, "Credit lines and the liquidity insurance channel," *Journal of Money, Credit and Banking*, 2021, *53* (5), 901–938.

**Agarwal, Isha and Matthew Baron**, "Inflation and Disintermediation," *Journal of Financial Economics*, 2024, *160*, 103902.

**Beutel, Johannes and Michael Weber**, "Beliefs and portfolios: Causal evidence," *Chicago Booth Research Paper*, 2022, (22-08).

**Brunnermeier, Markus K, Sergio A Correia, Stephan Luck, Emil Verner, and Tom Zimmermann**, "The Debt-Inflation Channel of the German Hyperinflation," *American Economic Review*, 2025, *115* (7), 2111–2150.

**Carvalho, Daniel, Janet Gao, and Pengfei Ma**, "Loan spreads and credit cycles: The role of lenders' personal economic experiences," *Journal of Financial Economics*, 2023, *148* (2), 118–149.

**Chava, Sudheer and Michael R Roberts**, "How does financing impact investment? The role of debt covenants," *The journal of finance*, 2008, *63* (5), 2085–2121.

**Cooperman, Harry, Darrell Duffie, Stephan Luck, Zachry Wang, and Yilin Yang**, "Bank funding risk, reference rates, and credit supply," *The Journal of Finance*, 2025, *80* (1), 5–56.

**D'Acunto, Francesco, Janet Gao, Lu Liu, Kai Lu, Zhengwei Wang, and Jun Yang**, "Subjective Expectations and Financial Intermediation," *Available at SSRN*, 2024.

**D'Andrea, Angelo, Andrea Fabiani, Fabio Piersanti, and Anatoli Segura**, "Inflation, Leverage and Stock Returns," *CEPR Discussion Paper No. 19966*, 2025.

**Fahlenbrach, Rüdiger, Robert Prilmeier, and René M Stulz**, "Why does fast loan growth predict poor performance for banks?," *The Review of Financial Studies*, 2018, *31* (3), 1014–1063.

**Fisher, Irving**, "The debt-deflation theory of great depressions," *Econometrica: Journal of the Econometric Society*, 1933, pp. 337–357.

**Friedheim, Diego**, "Lenders' Expectations and Sovereign Debt Crises Contagion," *Working Paper*, 2025.

**Giglio, Stefano, Matteo Maggiori, Johannes Stroebel, and Stephen Utkus**, "Five facts about beliefs and portfolios," *American Economic Review*, 2021, *111* (5), 1481–1522.

**Gomes, Joao, Urban Jermann, and Lukas Schmid**, "Sticky leverage," *American Economic Review*, 2016, *106* (12), 3800–3828.

**Greenwood, Robin and Samuel G Hanson**, "Issuer quality and corporate bond returns," *The Review of Financial Studies*, 2013, *26* (6), 1483–1525.

**Ippolito, Filippo, Ali K. Ozdagli, and Andres Perez-Orive**, "The transmission of monetary policy through bank lending: the floating rate channel," *Journal of Monetary Economics*, 2018, *95*, 49–71.

**Ivashina, Victoria**, "Structure and pricing of syndicated loans," in "The New York City area conference on financial intermediation," Vol. 18 2005.

**Kalemli-Ozcan, Sebnem and Liliana Varela**, "Five facts about the uip premium," Technical Report, National Bureau of Economic Research 2021.

**Keynes, JM**, *A Tract on Monetary Reform*, Macmillan, 1923.

**Kindleberger, Charles P**, "Manias, panics, and rationality," *Eastern Economic Journal*, 1978, *4* (2), 103–112.

**Li, Xiang and Steven Ongena**, "Global Banks' Macroeconomic Expectations and Credit Supply," *Available at SSRN 5287373*, 2025.

**Ma, Yueran, Teodora Paligorova, and José-Luis Peydro**, "Expectations and bank lending," *University of Chicago, Unpublished Working Paper*, 2021.

**Marco, Filippo De, Marco Macchiavelli, and Rosen Valchev**, "Beyond Home Bias: International Portfolio Holdings and Information Heterogeneity," *The Review of Financial Studies*, 2022, *35* (9), 4387–4422.

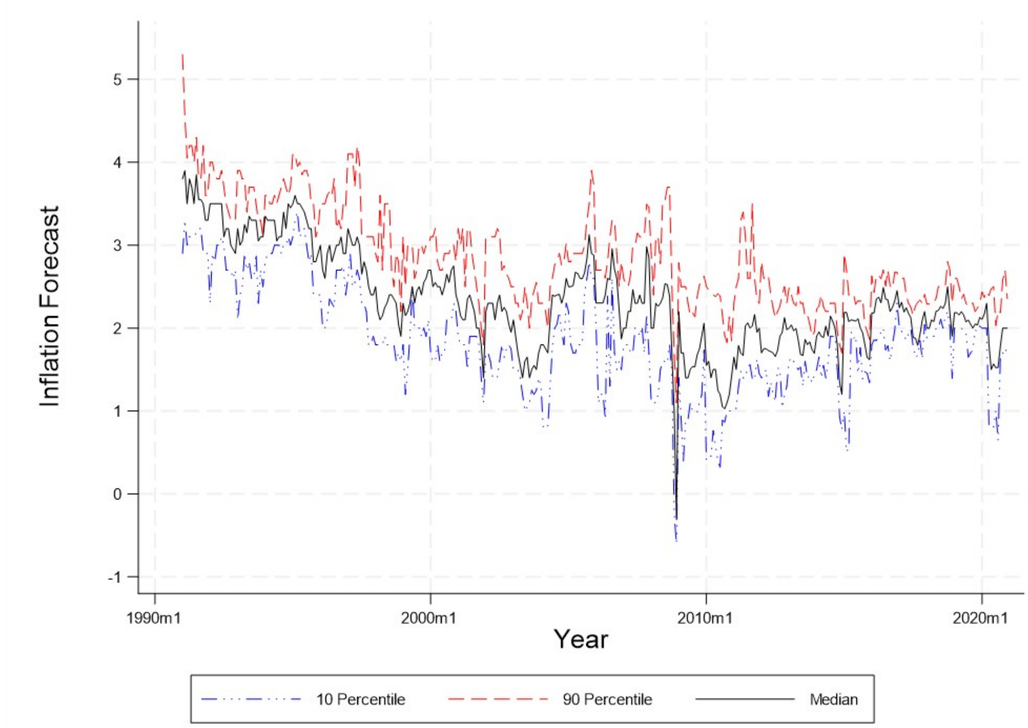
**Minsky, Hyman P**, "The financial instability hypothesis: An interpretation of Keynes and an alternative to" standard" theory," *Challenge*, 1977, *20* (1), 20–27.

**Ranaldi, Lorenzo**, "The Credit Channel of Inflation," *Working Paper*, 2025.

**Roberts, Michael R**, "The role of dynamic renegotiation and asymmetric information in financial contracting," *Journal of Financial Economics*, 2015, *116* (1), 61–81.

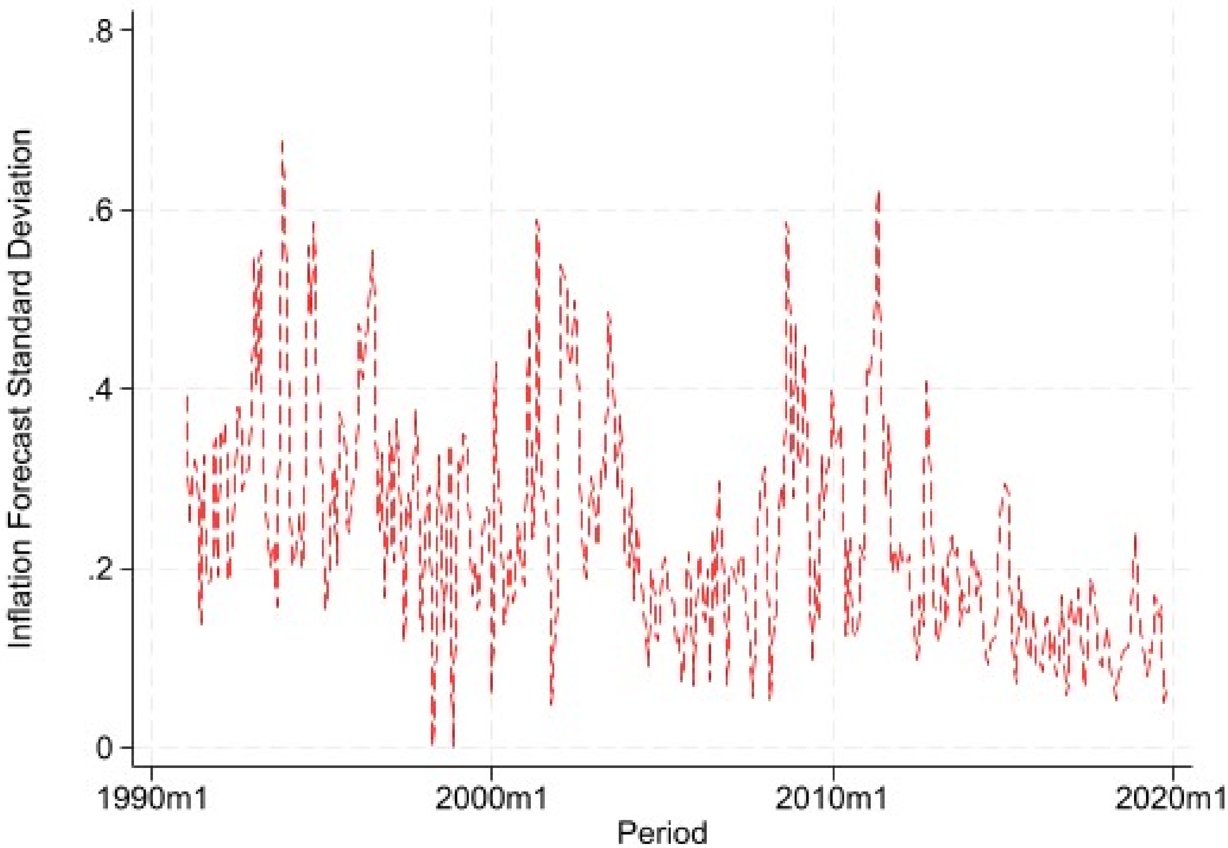
**Schwert, Michael**, "Does Borrowing from Banks Cost More than Borrowing from the Market?," *The Journal of Finance*, 2020, *75* (2), 905–947.

Figure 1: Inflation Expectations Dispersion




The figure plots the time-series of the percentile $10^{th}$ and $90^{th}$ and the median for banks in our sample.

Figure 2: 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 | 1.90 | 2.09 | 1.06 | 0.25 | 1.40 | 2.55 | 3.08 | 18,393 |
| GDP Forecast | 2.36 | 2.40 | 0.89 | 1.27 | 1.80 | 3.00 | 3.50 | 18,389 |
| Long Interest Rate Forecast | 3.95 | 4.47 | 2.17 | 1.05 | 1.88 | 5.53 | 6.50 | 17,377 |
| Short Interest Rate Forecast | 2.73 | 2.58 | 2.16 | 0.20 | 0.45 | 4.65 | 5.47 | 16,428 |
| **Panel B: LPC DealScan** | | | | | | | | |
| Deal Amount (USD mil) | 2392.60 | 400.00 | 9352.56 | 34.44 | 100.00 | 1500.00 | 5000.00 | 18,393 |
| Credit Line Amount (USD mil) | 2207.26 | 383.98 | 8384.48 | 30.00 | 100.00 | 1500.00 | 4510.86 | 14,555 |
| Term Line Amount (USD mil) | 1739.94 | 263.18 | 7705.52 | 25.00 | 75.00 | 1000.00 | 3306.16 | 6,828 |
| Credit Line Spread (bps) | 147.41 | 125.00 | 109.47 | 30.00 | 55.00 | 225.00 | 300.00 | 9,450 |
| Term Line Spread (bps) | 244.02 | 225.00 | 156.39 | 75.00 | 130.00 | 305.00 | 450.00 | 4,030 |
| Maturity (Months) | 44.53 | 47.00 | 25.57 | 12.00 | 21.00 | 60.00 | 72.00 | 17,375 |
| Maturity Credit (Months) | 39.29 | 36.00 | 21.67 | 12.00 | 12.00 | 60.00 | 60.00 | 13,663 |
| Maturity Term (Months) | 61.93 | 60.00 | 30.02 | 24.00 | 46.00 | 75.00 | 90.00 | 6,588 |
| **Panel C: Compustat (Global and North America)** | | | | | | | | |
| Capital Expenditure | 10564.01 | 214.89 | 38893.25 | 9.54 | 40.80 | 1493.00 | 13793.00 | 18,065 |
| Employment | 23.18 | 6.40 | 43.32 | 0.63 | 1.92 | 22.62 | 62.38 | 17,574 |
| Long Leverage | 0.52 | 0.47 | 0.38 | 0.06 | 0.25 | 0.72 | 1.00 | 18,379 |
| Short Leverage | 0.39 | 0.21 | 0.50 | 0.00 | 0.05 | 0.53 | 1.00 | 18,354 |
| Profitability | 0.11 | 0.11 | 0.07 | 0.04 | 0.07 | 0.15 | 0.20 | 18,291 |
| Tangibility | 0.34 | 0.29 | 0.24 | 0.07 | 0.15 | 0.51 | 0.73 | 18,345 |

This table reports summary statistics for all variables used in the empirical analysis. Panel A presents bank-level macroeconomic forecasts (inflation, GDP, long- and short-term interest rates) 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: Transition matrix and forecast correlations

**Panel A: Forecast correlations**

| | CPI growth | GDP growth | 3M rate | 10Y rate |
|---|---|---|---|---|
| CPI growth | 1.00 | 0.13 | 0.36 | 0.25 |
| GDP growth | 0.13 | 1.00 | 0.28 | 0.20 |
| 3M rate | 0.36 | 0.28 | 1.00 | 0.58 |
| 10Y rate | 0.25 | 0.20 | 0.58 | 1.00 |

Notes: This table presents the bank forecast correlation controlling by month-country fixed effects.

**Panel B: Transition matrix of inflation-forecast cluster per quintile**

| From \ To | G1 | G2 | G3 | G4 | G5 |
|---|---|---|---|---|---|
| G1 | 0.42 | 0.28 | 0.16 | 0.10 | 0.04 |
| G2 | 0.23 | 0.22 | 0.22 | 0.20 | 0.13 |
| G3 | 0.09 | 0.23 | 0.30 | 0.24 | 0.14 |
| G4 | 0.11 | 0.19 | 0.11 | 0.30 | 0.30 |
| G5 | 0.03 | 0.06 | 0.18 | 0.17 | 0.56 |

Notes: This table reports the transition matrix for banks sorted into annual inflation–forecast quintiles. Group 1 contains banks with the highest inflation forecasts in a given year, and Group 5 contains those with the lowest. Entries give the probability of moving from the row group in year $t$ to the column group in year $t+1$.

Table 3: Banks Inflation Forecast and Credit Line Amount

| | (1) Log Amount | (2) Log Amount | (3) Log Amount | (4) Log Amount |
|---|---|---|---|---|
| $\mathbb{E}(CPI^{y+1}) \times$ Lev | 0.20*** | 0.17*** | 0.17*** | 0.18*** |
| | (0.07) | (0.06) | (0.06) | (0.06) |
| $\mathbb{E}(CPI^{y+1})$ | -0.20* | -0.13 | -0.14 | -0.08 |
| | (0.11) | (0.12) | (0.12) | (0.12) |
| Lev | -0.47*** | -0.44*** | -0.37* | -0.40* |
| | (0.18) | (0.15) | (0.22) | (0.22) |
| $\mathbb{E}(GDP^{y+1})$ | | | 0.08 | 0.08 |
| | | | (0.07) | (0.07) |
| $\mathbb{E}(GDP^{y+1}) \times$ Lev | | | -0.02 | -0.02 |
| | | | (0.05) | (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 |
| $R^2$ | 0.81 | 0.85 | 0.85 | 0.85 |
| Observations | 12,651 | 12,231 | 12,226 | 12,120 |

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is at the deal level. The dependent variable is the credit line spread. The main coefficient of interest, reported in the first row, captures the interaction between firm (lagged) long leverage, i.e. the ratio of debt with over one year maturity over total assets, and bank inflation forecasts. All columns include firm and country–month fixed effects. Column (2) additionally includes industry–by–year fixed effects; Column (4) adds firm-level controls and their interactions with bank inflation forecasts. 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 Spread

| | (1) Spread | (2) Spread | (3) Spread | (4) Spread |
|---|---|---|---|---|
| $\mathbb{E}(CPI^{y+1})\times$ Lev | -16.96*** | -15.11*** | -14.85*** | -14.69*** |
| | (3.92) | (3.70) | (3.63) | (4.24) |
| $\mathbb{E}(CPI^{y+1})$ | 12.74** | 7.24 | 7.67 | -6.13 |
| | (5.42) | (5.57) | (5.36) | (6.18) |
| Lev | 67.68*** | 63.81*** | 55.13*** | 47.60** |
| | (11.92) | (11.74) | (19.62) | (20.59) |
| $\mathbb{E}(GDP^{y+1})$ | | | -5.30 | -6.22 |
| | | | (4.48) | (4.39) |
| $\mathbb{E}(GDP^{y+1})\times$ Lev | | | 2.82 | 4.15 |
| | | | (5.51) | (5.67) |
| 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 |
| $R^2$ | 0.76 | 0.83 | 0.84 | 0.84 |
| Observations | 7644 | 7138 | 7133 | 7050 |

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is at the deal level. The dependent variable is the credit line spread. The main coefficient of interest, reported in the first row, captures the interaction between firm (lagged) long leverage, i.e. the ratio of debt with over one year maturity over total assets, and bank inflation forecasts. All columns include firm and country–month fixed effects. Column (2) additionally includes industry–by–year fixed effects; Column (4) adds firm-level controls and their interactions with bank inflation forecasts. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 5: Robustness to Interest Rate Forecasts

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Log Amount | | Interest Rate Spread | |
| $\mathbb{E}(CPI^{y+1})\times$ Lev | 0.22*** | 0.17** | -23.67** | -22.70*** |
| | (0.08) | (0.06) | (10.25) | (4.50) |
| $\mathbb{E}(CPI^{y+1})$ | -0.19 | -0.16*** | 16.48** | 12.74* |
| | (0.12) | (0.05) | (7.70) | (7.03) |
| Lev | -0.85*** | -0.30 | 87.28*** | 52.61*** |
| | (0.26) | (0.24) | (28.87) | (18.66) |
| $\mathbb{E}(GDP^{y+1})$ | -0.02 | 0.09** | 0.42 | -7.16 |
| | (0.06) | (0.03) | (4.16) | (6.19) |
| $\mathbb{E}(GDP^{y+1})\times$ Lev | 0.09* | -0.03 | -2.76 | 2.78 |
| | (0.05) | (0.03) | (5.08) | (5.56) |
| $\mathbb{E}(3M^{y+1})$ | -0.03 | | -3.42 | |
| | (0.10) | | (4.68) | |
| $\mathbb{E}(3M^{y+1})\times$ Lev | 0.01 | | 2.06 | |
| | (0.02) | | (3.25) | |
| $\mathbb{E}(10Y^{y+1})$ | | 0.07 | | -4.14 |
| | | (0.04) | | (4.06) |
| $\mathbb{E}(10Y^{y+1})\times$ Lev | | -0.02 | | 6.12** |
| | | (0.01) | | (2.43) |
| Firm FE | Yes | Yes | Yes | Yes |
| Country Time FE | Yes | Yes | Yes | Yes |
| Industry Time FE | Yes | Yes | Yes | Yes |
| $R^2$ | 0.82 | 0.87 | 0.76 | 0.85 |
| Observations | 10355 | 10724 | 6470 | 5978 |

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 (lagged) long leverage, i.e. the ratio of debt with over one year maturity over total assets, and bank inflation forecasts. All columns include firm and country–month fixed effects, as well as industry–by–year fixed effects. *Clustering choice:* Column (3) reports standard errors clustered at the bank–country level, while Columns (1), (2), and (4) use two–way clustering by bank and country. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 6: Short-term vs. Long-term leverage

| **Panel A: Log Credit Line Amount** | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\mathbb{E}(CPI^{y+1})\times$ Long Leverage | 0.20*** | 0.17** | 0.17** | 0.18*** |
| | (0.07) | (0.07) | (0.07) | (0.07) |
| $\mathbb{E}(CPI^{y+1})\times$ Short Leverage | -0.04 | -0.04 | -0.03 | -0.04 |
| | (0.02) | (0.03) | (0.03) | (0.03) |
| 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 |
| $R^2$ | 0.81 | 0.85 | 0.85 | 0.85 |
| Observations | 12613 | 12197 | 12192 | 12098 |

| **Panel B: Credit Line Spread** | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\mathbb{E}(CPI^{y+1})\times$ Long Leverage | -17.56*** | -16.88*** | -16.57*** | -15.88*** |
| | (1.33) | (4.60) | (4.39) | (4.29) |
| $\mathbb{E}(CPI^{y+1})\times$ Short Leverage | -3.49*** | -6.05 | -5.66 | -2.95 |
| | (1.01) | (7.17) | (6.62) | (7.10) |
| 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 |
| $R^2$ | 0.76 | 0.84 | 0.84 | 0.84 |
| Observations | 7630 | 7127 | 7122 | 7043 |

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is at the deal level. In Panel A (top panel), the dependent variable is the log of the credit line amount, while in Panel B (bottom panel) it is the credit line spread. Long Leverage is the firm (lagged) long leverage, i.e. the ratio of debt with over one year maturity over total assets, while Short Leverage is the ratio of debt below one year maturity over total assets. All regressions include firm and country–month fixed effects. Panel A reports standard errors clustered at the bank–country level, whereas Panel B uses two-way clustering by bank and country. Columns (2)–(4) additionally incorporate industry–by–year fixed effects, and Columns (3)–(4) include bank GDP forecast controls. The last column in each panel also includes firm-level controls (such as profitability) and their interaction with bank inflation forecasts. Errors are clustered at the bank–country level. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 7: Next-period leverage

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Leverage$_{y+1}$ | | | |
| $\mathbb{E}(CPI^{y+1}) \times \text{Lev}_{y-1}$ | -0.02$^{***}$ | -0.02$^{***}$ | -0.02$^{***}$ | -0.02$^{***}$ |
| | (0.00) | (0.01) | (0.00) | (0.00) |
| $\mathbb{E}(CPI^{y+1})$ | 0.01$^{***}$ | 0.01$^{*}$ | 0.01$^{***}$ | 0.00 |
| | (0.00) | (0.01) | (0.00) | (0.01) |
| Long Lev$_{y-1}$ | 0.21$^{***}$ | 0.21$^{***}$ | 0.22$^{***}$ | 0.22$^{***}$ |
| | (0.01) | (0.02) | (0.02) | (0.02) |
| $\mathbb{E}(GDP^{y+1})$ | | | 0.00$^{*}$ | 0.00$^{*}$ |
| | | | (0.00) | (0.00) |
| $\mathbb{E}(GDP^{y+1}) \times \text{Lev}_{y-1}$ | | | -0.00 | -0.00 |
| | | | (0.01) | (0.01) |
| Short Leverage | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Country Time FE | Yes | Yes | Yes | Yes |
| Industry Time FE | No | Yes | Yes | Yes |
| Industry Time FE | No | No | No | Yes |
| $R^2$ | 0.83 | 0.86 | 0.86 | 0.86 |
| Observations | 11,340 | 10,923 | 10,918 | 10,839 |

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is at the firm $f$ in year $y$. The dependent variable is the following year total leverage. 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 short term leverage and its interaction with bank forecasts (CPI and GDP) as control and firm and country–year fixed effects. Column (2) additionally includes industry–by–year fixed effects; Column (4) adds firm-level controls (such as profitability) and their interactions with bank inflation forecasts. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table 8: Banks Inflation Forecast, Bond Issuance

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Log(Bond Amount Issued)$_{t+2,t+1}$ | | | |
| $\mathbb{E}(CPI^{y+1}) \times$ Lev | -0.08 | -0.27$^{**}$ | -0.26$^{*}$ | -0.28$^{**}$ |
| | (0.11) | (0.13) | (0.14) | (0.14) |
| $\mathbb{E}(CPI^{y+1})$ | 0.03 | 0.20$^{*}$ | 0.18 | 0.26$^{*}$ |
| | (0.09) | (0.12) | (0.12) | (0.13) |
| Lev | -0.05 | 0.27 | 0.69$^{*}$ | 0.73$^{**}$ |
| | (0.21) | (0.24) | (0.35) | (0.35) |
| $\mathbb{E}(GDP^{y+1})$ | | | 0.23$^{***}$ | 0.23$^{***}$ |
| | | | (0.07) | (0.07) |
| $\mathbb{E}(GDP^{y+1}) \times$ Lev | | | -0.15$^{**}$ | -0.16$^{**}$ |
| | | | (0.07) | (0.07) |
| Firm FE | Yes | Yes | Yes | Yes |
| Country Time FE | No | Yes | Yes | Yes |
| Short Leverage Controls | No | No | No | Yes |
| $R^2$ | 0.74 | 0.81 | 0.81 | 0.81 |
| Observations | 492 | 460 | 460 | 457 |

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is at the firm $f$ in year $y$. The dependent variable is the logaritmic of the bond amoount of the firs emision in the following two years after obtaining a deal. The main coefficient of interest, reported in the first row, captures the interaction between firm Lev (lagged one year) and bank inflation forecasts. All columns include firm fixed effects. Column (2) additionally includes country–year fixed effects; Column (3) adds bank GDP forecast and its interaction with Lev; Column (4) adds short term leverage and its interaction with bank inflation forecast as a control. Standard errors are clustered at the firm 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.[13] Then we connect this database with the current one through the "LoanConnector" provided by WRDS.[14] As a result, we obtain the current LPC Dealscan with a company ID ($gvkey$) which

[13]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.

[14]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.[15]

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.

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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

[15]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.

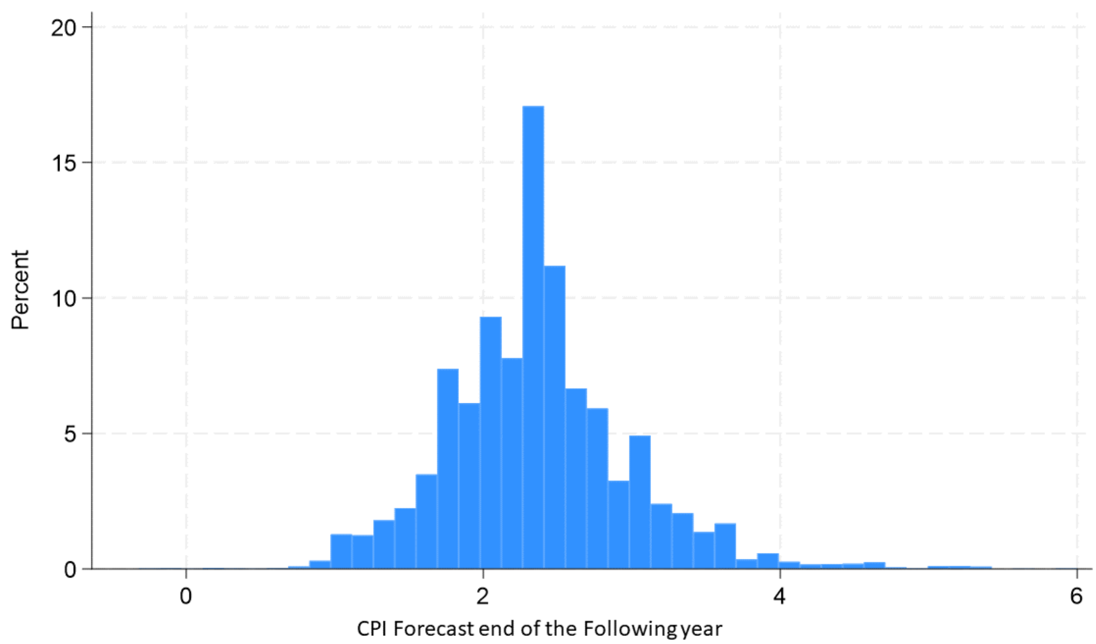



Figure A1: CPI Forecast Histogram (US and Canada)

Figure A1 shows a relevant dispersion of CPI forecasts for US and Canada, going from 1% to 4%, in line with Figure 2 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 | Total forecasts | Top country | Forecasts in top | Share (%) |
|---|---|---|---|---|
| Bank of Tokyo-Mitsubishi UFJ | 6081 | Japan | 6081 | 100.0 |
| Bank of America | 6071 | United States | 5904 | 97.2 |
| JP Morgan | 4789 | United States | 4428 | 92.5 |
| Mizuho Securities | 3589 | Japan | 3589 | 100.0 |
| Wachovia Corp | 2755 | United States | 2755 | 100.0 |
| Wells Fargo | 2419 | United States | 2419 | 100.0 |
| Citigroup | 1878 | United States | 1466 | 78.1 |
| NationsBank | 1608 | United States | 1608 | 100.0 |
| Credit Suisse | 1048 | United States | 946 | 90.3 |
| HSBC | 942 | United Kingdom | 480 | 51.0 |
| Chemical Bank | 896 | United States | 896 | 100.0 |
| Chase | 853 | United States | 804 | 94.3 |
| Bank One Corp | 827 | United States | 827 | 100.0 |
| Northern Trust | 755 | United States | 755 | 100.0 |
| Goldman Sachs | 748 | United States | 655 | 87.6 |
| Morgan Stanley | 667 | United States | 623 | 93.4 |
| Merrill Lynch | 585 | United States | 554 | 94.7 |
| Royal Bank of Canada | 570 | Canada | 552 | 96.8 |
| CIBC | 524 | Canada | 520 | 99.2 |
| RBS | 514 | United Kingdom | 508 | 98.8 |
| Continental Bank | 426 | United States | 426 | 100.0 |
| Toronto Dominion | 402 | Canada | 402 | 100.0 |
| BNP Paribas | 360 | France | 226 | 62.8 |
| Lehman Brothers | 358 | United States | 349 | 97.5 |
| Barclays | 345 | United Kingdom | 260 | 75.4 |
| Bankers Trust | 335 | United States | 335 | 100.0 |
| ING | 277 | United Kingdom | 128 | 46.2 |
| UBS | 258 | United States | 131 | 50.8 |
| Deutsche Bank | 235 | Germany | 131 | 55.7 |
| Bank of Montreal | 205 | Canada | 205 | 100.0 |

**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 Expectations Dispersion

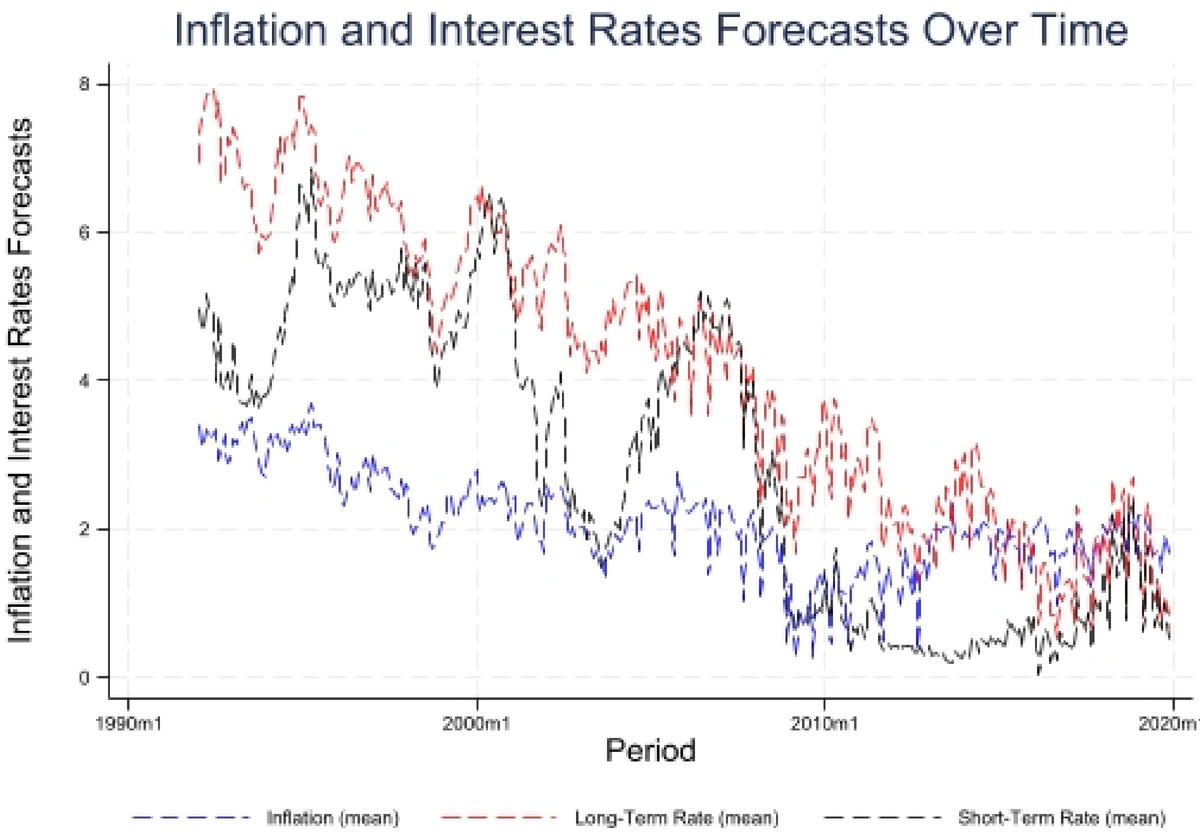


Figure A3: Inflation Expectations Dispersion

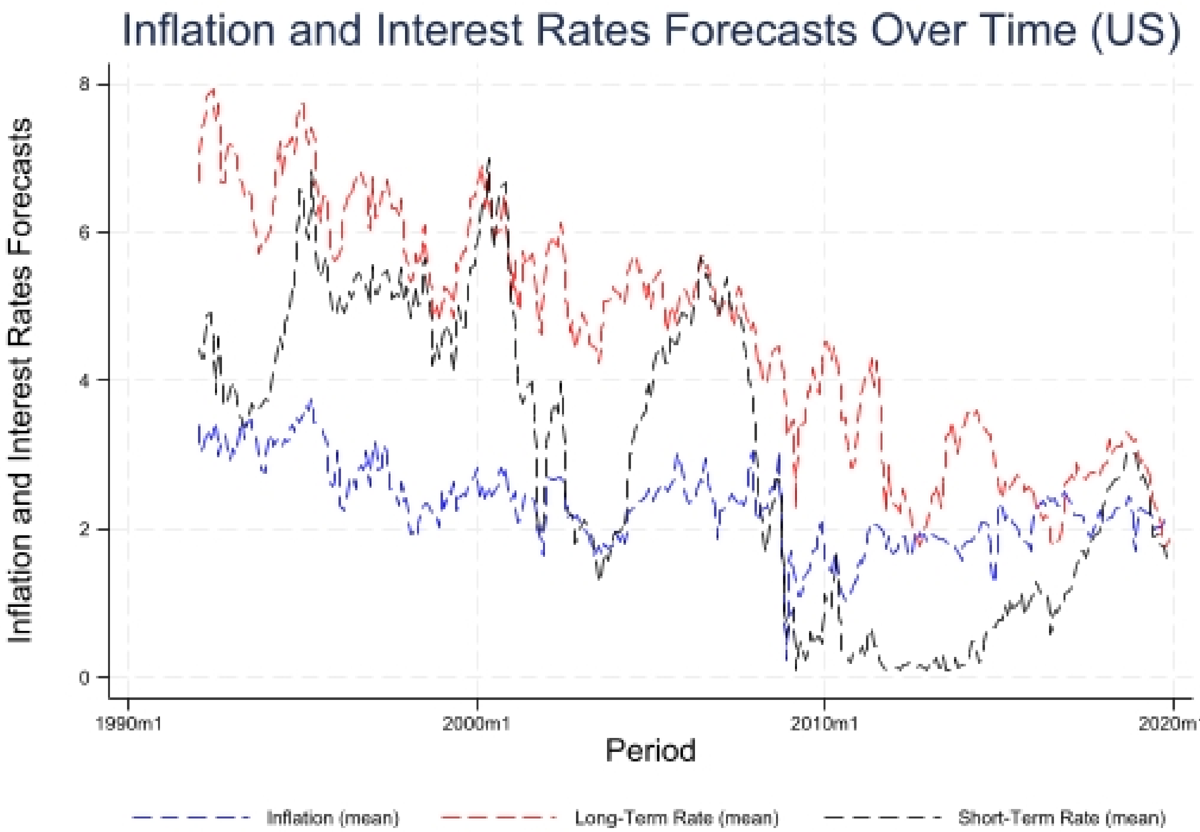
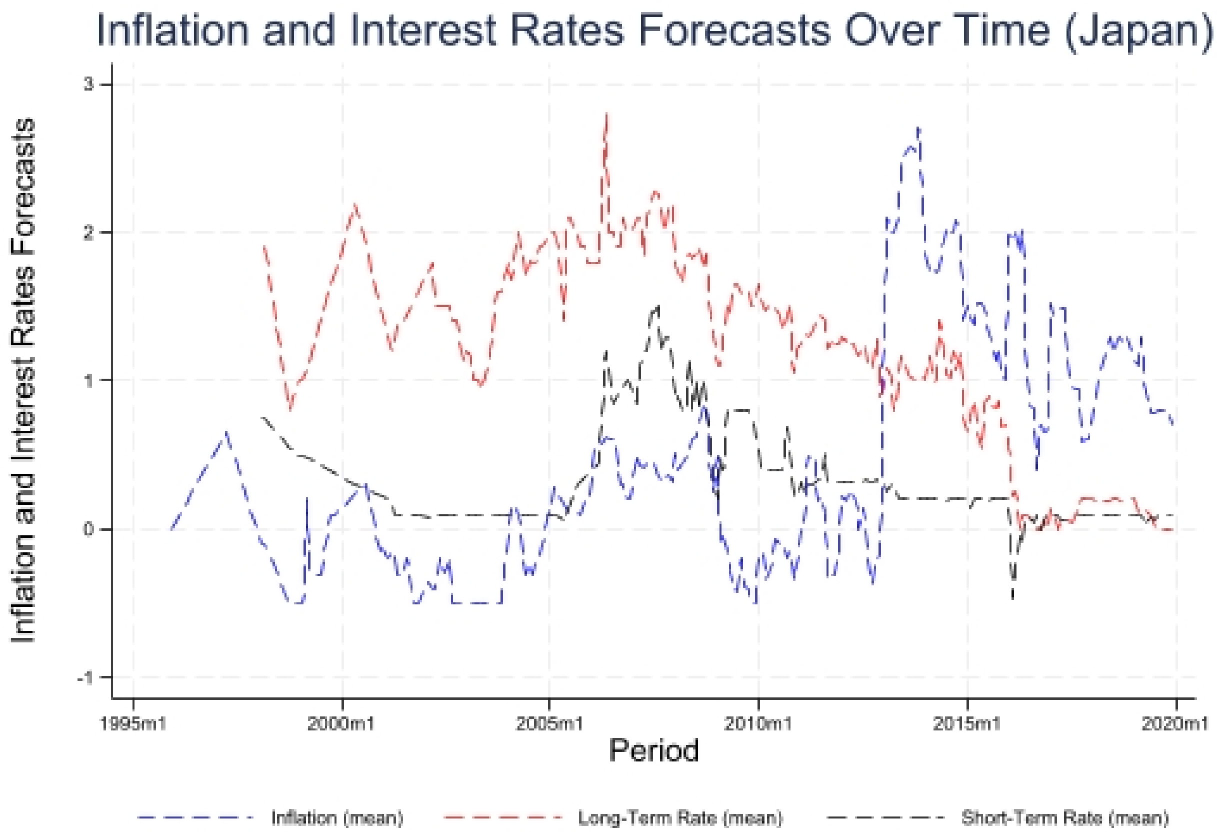


Figure A4: Inflation Expectations Dispersion



## 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:

$$L_{b,f,c,k,t} = \beta_1 \mathbb{E}(CPI_{b,c,t}^{y+1}) + \beta_2 \mathbb{E}(CPI_{b,c,t}^{y+1}) \times Lev_{f,y-1} + \gamma GDP_{b,c,t}^{y+1} + \gamma_2 GDP_{b,c,t}^{y+1} \times Lev_{f,y-1} \tag{4}$$

$$+ \omega_{c,t} + \omega_f + \omega_{k,y} + \chi_{f,y-1} + \epsilon_{b,f,c,k,t},$$

As in Section 3, the coefficient of interest is again the interaction between bank inflation expectations, $\mathbb{E}(CPI_{b,c,t}^{y+1})$, 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.

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

| | (1) Log Amount | (2) Log Amount | (3) Log Amount | (4) Log Amount |
|---|---|---|---|---|
| $CPI^f$ × Long Leverage | 0.26*** | 0.20* | 0.19* | 0.19* |
| | (0.07) | (0.10) | (0.10) | (0.10) |
| $CPI^f$ | -0.26* | -0.15 | -0.17 | 0.00 |
| | (0.13) | (0.14) | (0.14) | (0.14) |
| Long Leverage | -0.63*** | -0.45* | -0.28 | -0.30 |
| | (0.14) | (0.24) | (0.33) | (0.36) |
| $GDP^f$ | | | 0.15* | 0.14 |
| | | | (0.08) | (0.09) |
| $GDP^f$ × Leverage | | | -0.05 | -0.04 |
| | | | (0.06) | (0.07) |
| 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 | 0.82 | 0.82 | 0.82 |
| Observations | 7,944 | 7,497 | 7,492 | 7,415 |

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

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

| | (1) Log Amount | (2) Log Amount | (3) Log Amount | (4) Log Amount |
|---|---|---|---|---|
| $CPI^f$ × Long Leverage | 0.01 | 0.12*** | 0.09*** | 0.09** |
| | (0.04) | (0.03) | (0.03) | (0.03) |
| $CPI^f$ | -0.07 | -0.01 | 0.02 | 0.03 |
| | (0.06) | (0.07) | (0.08) | (0.08) |
| Long Leverage | 0.16 | -0.13 | 0.25*** | 0.21*** |
| | (0.10) | (0.13) | (0.06) | (0.05) |
| $GDP^f$ | | | 0.15*** | 0.15*** |
| | | | (0.03) | (0.03) |
| $GDP^f$ × Leverage | | | -0.21** | -0.21** |
| | | | (0.06) | (0.07) |
| 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 |
| $R^2$ | 0.90 | 0.93 | 0.93 | 0.93 |
| Observations | 2,568 | 2,301 | 2,301 | 2,298 |

Note: Standard errors in parentheses, clustered at the bank-country 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 |
|---|---|---|---|---|
| $CPI^f$ × Long Leverage | -17.29*** | -14.78*** | -14.43*** | -13.86*** |
| | (5.34) | (4.41) | (4.37) | (4.18) |
| $CPI^f$ | 14.30*** | 8.37 | 8.72 | -6.91 |
| | (5.20) | (5.99) | (6.06) | (7.48) |
| Long Leverage | 68.54*** | 61.97*** | 51.20** | 43.24** |
| | (15.13) | (13.35) | (21.94) | (21.00) |
| $GDP^f$ | | | -5.94 | -6.64 |
| | | | (5.05) | (4.87) |
| $GDP^f$ × Leverage | | | 3.47 | 4.63 |
| | | | (5.70) | (5.65) |
| 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 | 0.83 | 0.83 | 0.83 |
| Observations | 6,887 | 6,395 | 6,390 | 6,339 |

Note: Standard errors in parentheses, clustered at the bank-country 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 and A6 show that the results for this subsample are similar to those obtained with the full sample.

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

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Log Amount | Log Amount | Log Amount | Log Amount |
| $CPI^f \times$ Long Leverage | 0.32*** | 0.27** | 0.26** | 0.24** |
| | (0.09) | (0.11) | (0.11) | (0.10) |
| $CPI^f$ | -0.32** | -0.22 | -0.23 | 0.03 |
| | (0.16) | (0.17) | (0.18) | (0.19) |
| Long Leverage | -0.83*** | -0.71*** | -0.50 | -0.43 |
| | (0.24) | (0.27) | (0.39) | (0.38) |
| $GDP^f$ | | | 0.09 | 0.08 |
| | | | (0.09) | (0.09) |
| $GDP^f \times$ Leverage | | | -0.06 | -0.06 |
| | | | (0.06) | (0.07) |
| 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 |
| $R^2$ | 0.80 | 0.84 | 0.84 | 0.84 |
| Observations | 7073 | 6875 | 6870 | 6799 |

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. Column (2) additionally includes industry–by–year fixed effects; Column (4) adds firm-level controls and their interactions with bank inflation forecasts. *Clustering choice:* Columns (1)–(2) report standard errors clustered at the bank–country level because two-way clustering by bank and country did not converge for those specifications; Columns (3)–(4) use two-way clustering by bank and country. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Table A6: Banks´ Inflation Forecast and Credit Line Spread Pre-Crisis

| | (1) Spread | (2) Spread | (3) Spread | (4) Spread |
|---|---|---|---|---|
| $CPI^f$ × Long Leverage | -18.31*** | -17.46*** | -17.37*** | -14.59** |
| | (5.68) | (4.99) | (4.78) | (5.88) |
| $CPI^f$ | 19.35*** | 15.17* | 15.88** | 0.91 |
| | (7.14) | (7.75) | (7.65) | (8.06) |
| Long Leverage | 65.68*** | 66.56*** | 70.15*** | 54.04** |
| | (14.30) | (14.96) | (20.14) | (22.92) |
| $GDP^f$ | | | -1.61 | -2.90 |
| | | | (5.68) | (5.64) |
| $GDP^f$ × Long Leverage | | | -1.32 | 0.62 |
| | | | (5.93) | (6.28) |
| 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 | 0.84 | 0.84 | 0.84 |
| Observations | 5,460 | 5,221 | 5,216 | 5,150 |

Note: Standard errors in parentheses, clustered at the bank-country 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 A7 confirms that this is indeed the case.

Table A7: Banks Inflation Forecast and Deal Amount

| | (1) Log Deal Amount | (2) Log Deal Amount | (3) Log Deal Amount | (4) Log Deal Amount |
|---|---|---|---|---|
| $CPI^f$ × Long Leverage | 0.13** | 0.10* | 0.10* | 0.11** |
| | (0.06) | (0.06) | (0.05) | (0.05) |
| $CPI^f$ | -0.20** | -0.14 | -0.13** | -0.11*** |
| | (0.09) | (0.09) | (0.04) | (0.03) |
| Long Leverage | -0.29* | -0.26* | -0.19 | -0.17 |
| | (0.15) | (0.15) | (0.33) | (0.32) |
| $GDP^f$ | | | -0.02 | -0.02 |
| | | | (0.04) | (0.04) |
| $GDP^f$ × Long Leverage | | | -0.03 | -0.03 |
| | | | (0.07) | (0.07) |
| 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 | 16,609 | 16,255 | 16,247 | 16,095 |

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

Along the paper We focus in the spread as the main rate banks charge over their lines because is the most important one. Still we find similar results looking at other rate like the margin firms need to pay over the line. Table A8 shows that we observe similar effects on this margin.

Tables A9 and A10 show that including all deals in the sample (also including amended deals), we have results in line with the main definition.

Table A8: Banks Inflation Forecast and Margin Credit Line

| | (1) Margin | (2) Margin | (3) Margin | (4) Margin |
|---|---|---|---|---|
| $CPI^f \times$ Long Leverage | -13.09*** | -14.35*** | -14.17*** | -12.36*** |
| | (2.71) | (4.27) | (4.20) | (4.23) |
| $CPI^f$ | 8.58** | 5.52 | 6.50 | -16.35* |
| | (3.90) | (5.02) | (5.26) | (9.53) |
| Long Leverage | 59.45*** | 61.66*** | 56.71*** | 45.87*** |
| | (7.80) | (12.08) | (12.36) | (12.97) |
| $GDP^f$ | | | -7.38 | -8.34* |
| | | | (5.05) | (4.96) |
| $GDP^f \times$ Long Leverage | | | 1.57 | 2.91 |
| | | | (2.75) | (2.94) |
| 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 | 0.84 | 0.84 | 0.84 |
| Observations | 7,629 | 7,117 | 7,112 | 7,030 |

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

Table A9: Banks Inflation Forecast and Loans' Amount (Including Amended Deals)

| | (1) Log Amount | (2) Log Amount | (3) Log Amount | (4) Log Amount |
|---|---|---|---|---|
| $CPI^f \times$ Long Leverage | 0.20*** | 0.15*** | 0.15*** | 0.15*** |
| | (0.06) | (0.06) | (0.06) | (0.06) |
| $CPI^f$ | -0.21* | -0.14 | -0.14 | -0.08 |
| | (0.11) | (0.11) | (0.12) | (0.13) |
| Long Leverage | -0.52*** | -0.39*** | -0.36* | -0.35** |
| | (0.14) | (0.14) | (0.18) | (0.17) |
| $GDP^f$ | | | 0.05 | 0.05 |
| | | | (0.07) | (0.07) |
| $GDP^f \times$ Long Leverage | | | -0.01 | -0.01 |
| | | | (0.04) | (0.04) |
| 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 |
| $R^2$ | 0.78 | 0.81 | 0.81 | 0.81 |
| Observations | 18,044 | 17,701 | 17,697 | 17,527 |

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

Table A10: Banks Inflation Forecast and Credit Line Spread (Including Amended Deals)

| | (1) Spread | (2) Spread | (3) Spread | (4) Spread |
|---|---|---|---|---|
| $CPI^f \times$ Long Leverage | -14.38*** | -8.87*** | -9.22*** | -10.56*** |
| | (2.56) | (2.74) | (2.86) | (2.59) |
| $CPI^f$ | 8.58* | -0.77 | -0.48 | -9.85 |
| | (4.73) | (6.18) | (6.10) | (7.13) |
| Long Leverage | 62.74*** | 50.59*** | 42.25*** | 41.92*** |
| | (6.56) | (7.33) | (10.40) | (10.97) |
| $GDP^f$ | | | -2.96 | -2.98 |
| | | | (3.95) | (3.99) |
| $GDP^f \times$ Leverage | | | 3.24 | 3.43 |
| | | | (3.28) | (3.29) |
| 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 |
| $R^2$ | 0.72 | 0.78 | 0.78 | 0.79 |
| Observations | 12293 | 11821 | 11817 | 11693 |

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; Column (2) additionally includes industry–by–year fixed effects; Column (4) adds firm-level controls (such as profitability) and their interactions 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.

We find that banks expecting higher inflation shorten the maturity of credit lines. A similar pattern holds for term loans: Table A11 shows that banks with higher inflation expectations also extend term loans with shorter maturities.

Table A11: Banks Inflation Forecast and Log Term Loan Maturity

| | (1)<br>log(Maturity) | (2)<br>log( Maturity) | (3)<br>log( Maturity) | (4)<br>log(Maturity) |
|---|---|---|---|---|
| $CPI^f \times$ Long Leverage | -0.09* | -0.05 | -0.06 | -0.07 |
| | (0.05) | (0.04) | (0.04) | (0.05) |
| $CPI^f$ | 0.09*** | -0.02 | -0.01 | -0.01 |
| | (0.02) | (0.03) | (0.03) | (0.02) |
| Long Leverage | 0.21 | 0.22 | 0.00 | -0.00 |
| | (0.13) | (0.16) | (0.16) | (0.17) |
| $GDP^f$ | | | -0.06 | -0.07 |
| | | | (0.05) | (0.05) |
| $GDP^f \times$ Long Leverage | | | 0.09*** | 0.10*** |
| | | | (0.02) | (0.02) |
| 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 |
| $R^2$ | 0.66 | 0.79 | 0.79 | 0.80 |
| Observations | 4,374 | 3,779 | 3,762 | 3,734 |

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 term line maturity. 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. Column (2) additionally includes industry–by–year fixed effects; Column (4) adds firm-level controls and their interactions with bank inflation forecasts. Standard errors clustered at the bank–country level. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

As a robustness check, we show that our results remain after introducing more granular fixed effects at the industry–country–month level. We then push further and estimate a specification with firm–year fixed effects, which absorb any shocks at the firm–year level. Table A12 reports the results.

Table A12: Banks Inflation Forecast and Credit Line Amount (Firm Year Fixed Effects)

| | (1) Log Amount | (2) Log Amount | (3) Log Amount |
|---|---|---|---|
| $CPI^f$ × Long Leverage | 0.58* | 0.49** | 0.47** |
| | (0.29) | (0.20) | (0.21) |
| $CPI^f$ | -0.35 | -0.27 | -0.23 |
| | (0.20) | (0.17) | (0.28) |
| $GDP^f$ | | -0.25 | -0.28 |
| | | (0.21) | (0.22) |
| $GDP^f$ × Long Leverage | | 0.32 | 0.34 |
| | | (0.25) | (0.27) |
| Firm-Year FE | Yes | Yes | Yes |
| Firm Controls | No | No | Yes |
| $R^2$ | 0.80 | 0.80 | 0.80 |
| Observations | 2,568 | 2,567 | 2,548 |

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-year fixed effects. Column (3) adds firm-level controls and their interactions with bank inflation forecasts. Standard errors clustered at the bank–country level. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

In this specification, the coefficient of interest is more than twice as large as in the main specification (Table 3); that is, comparing the same firm within the same year yields a stronger effect. However, this design restricts the sample to firms with multiple deals in a given year, resulting in a substantially smaller sample. Consequently, comparisons with the baseline estimates should be interpreted with caution.

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 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.[16]

$$L_{b,f,c,k,t} = \beta_1 long\ Lev_{f,y-1} + \beta_2 \mathbb{E}(CPI^{y+1}_{b,c,t}) + \beta_3 \mathbb{E}(CPI^{y+1}_{b,c,t}) \times long\ Lev_{f,y-1}$$
$$+ \omega_f + \omega_{k,t,c} + \chi_{f,y-1} + \chi_{f,y-1} \times \mathbb{E}(CPI^{y+1}_{b,c,t}) + \epsilon_{b,f,c,k,t}, \quad (5)$$

since Equation 5 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 A13 reports the results from this extended specification. Column 1 shows the log amount of the credit line as the dependent variable, and Column 2 shows 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.

[16]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.

Table A13: Credit Loan Amount and Spread with extra FE

| | (1) Log Amount | (2) Spread |
|---|---|---|
| $CPI^{y+1} \times$ Long Leverage | 0.24*** | -18.15*** |
| | (0.09) | (5.23) |
| $CPI^{y+1}$ | -0.14 | 10.63* |
| | (0.11) | (5.99) |
| Long Leverage | -0.51 | 67.04*** |
| | (0.36) | (22.60) |
| $GDP^{y+1}$ | 0.09 | -3.93 |
| | (0.07) | (6.40) |
| $GDP^{y+1} \times$ Long Leverage | -0.03 | 0.71 |
| | (0.06) | (5.35) |
| Firm FE | Yes | Yes |
| Firm Controls | Yes | Yes |
| Industry $\times$ Country $\times$ Month FE | Yes | Yes |
| $R^2$ | 0.86 | 0.84 |
| Observations | 9570 | 5835 |

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is at the deal level. The dependent variable is the credit line amount in logs in column (1), and the spread in column (2). 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 regressions include firm fixed effects, firm-level controls, and a full set of industry–country–month fixed effects. Standard errors are clustered at the bank–country level. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.