Information Spreads*

Antonio Falato† Joseph Kaboski‡ Jasmine Xiao§

March 2026

Abstract

We propose a financially-driven business cycle propagation mechanism in which firm credit spreads arise from default concerns under incomplete information. Rational, risk-neutral investors learn from public information but adjust expectations about firm creditworthiness downward incompletely in response to a deterioration in the profit outlook or increase in uncertainty. This leads to an endogenous correlation between default probabilities and recovery rates. Empirically, we show that spreads and real outcomes – both at the aggregate and firm-level – respond predictably to the new information summarized in professional forecast revisions. Quantitatively, the model explains the high levels and variation of credit spreads, as well as their patterns in response to public information, and establishes a novel amplification mechanism whereby credit spreads transmit changes in public information and its uncertainty to investment and the real economy.

JEL codes: E32, E44, G12

Keywords: learning, credit market volatility, business cycles

*The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Board of Governors or the Federal Reserve System. For helpful comments and suggestions, we thank George-Marios Angeletos, Cristina Arellano, Leonardo Elias (discussant), Zhen Huo, Joao Gomes, Francois Gourio, Robin Greenwood, Dejanir Silva (discussant), Egon Zakrajšek (discussant), and seminar and conference participants at Barcelona Summer Forum, Bank of Finland-CEPR Joint Conference on Monetary Economics and Reality, Copenhagen Business School, Econometric Society Meetings & World Congress, Expectations in Dynamic Macroeconomic Models Workshop, Federal Reserve Banks of Chicago & Minneapolis, ITAM, Macro-Finance Society Meeting (Chicago), Northwestern University, Oxford-NY Fed-BoE Monetary Economics Conference, Salento Macro Meeting, SED (Copenhagen), University of Amsterdam, University of Michigan, University of Notre Dame, and University of Nottingham.

†Federal Reserve Board. Email: antonio.falato@frb.gov.

‡University of Notre Dame, NBER & CEPR. Email: jkaboski@nd.edu.

§University of Amsterdam. Email: y.xiao2@uva.nl.

1 Introduction

Business cycles are investment driven, and an important driver of investment is in turn the cost of firm financing (Fazzari, Hubbard, and Petersen, 1988). Over the business cycle and across firms, much of the variation in the cost of firm financing reflects variation in the credit spreads paid by firms (Gilchrist and Zakrajšek, 2012; López-Salido, Stein, and Zakrajšek, 2017), and these spreads are in turn predictive of real economic activity. There is therefore a coherent theory of credit cycles in which spreads drive investment, and investment drive business cycles. However, the determinants of credit spreads are poorly understood, as spreads diverge from what is empirically explained by default risk, and the measured divergence of is strongly predictive of the business cycle (Collin-Dufresn, Goldstein, and Martin, 2001; Driessen, 2005; Gilchrist and Zakrajšek, 2012). These failures draw the coherence of the overall theory of credit cycles into question: if we have a mechanism to explain the high level and variation of spreads, will these spreads still have the predicted impact on the macroeconomy in an aggregate model?

To account for the high level and cyclical volatility of spreads, existing macro theory typically relies on investors having either time-varying risk appetite (e.g., Krishnamurthy and Li, 2025) or distorted beliefs (e.g., Bordalo et al., 2018). This paper develops and evaluates exactly an alternative, but potentially complementary, mechanism and its macroeconomic implications. We explain credit spreads as arising from default concerns under incomplete information. Specifically, to abstract from existing explanation, we model risk-neutral agents who are rational but imperfectly informed, having only signals of future profitability. These signals, whether firm-specific or aggregate, therefore also inform the price of debt: spreads correspondingly respond to shocks to both the mean and dispersion of these signals. When signals are bad, for example, firms and investors scale back investment and credit but not as strongly as under perfect information. If realized profitability is indeed low, default is therefore deeper than under perfect information, and so a covariance between expected default and losses conditional on default arises, elevating both the level and volatility of spreads. Theoretically, we develop this mechanism in a quantitative macroeconomic model with default. Empirically, using revisions in professional forecasts as our measure of signals, we show that the data – both at the aggregate and firm-level – are consistent with agents having imperfect information and therefore responding in predictable ways to new signals as the theory suggests. Quantitatively, we show that model simulations reproduce these regression results, again at both the aggre-

gate and firm-level. Moreover, the model establishes a novel amplification mechanism whereby credit spreads transmit changes in public information and its uncertainty to investment and exacerbates aggregate volatility. The model appears to generate volatile "excess bond premia", measured in the standard (i.e., Gilchrist and Zakrajšek, 2012) way, but no real premium actually exists: the measured premia reflect the time-varying expected recovery rates conditional on default.

We model our mechanism formally by introducing learning by uninformed debt-market investors into an otherwise standard business cycle model with defaultable long-term debt. Specifically, we imbed our mechanism into a standard infinite-horizon, discrete-time stochastic environment with value-maximizing investment and financing decisions under incomplete markets. There are two key ingredients to the mechanism: first, credit-market investors are uninformed about firm creditworthiness; second, they form beliefs about it by learning from publicly-available information predicting quarter-ahead corporate profits. These two stark ingredients lead to a novel amplification mechanism: when investors observe a deterioration in the short-term profit outlook, they become pessimistic about firm default risk and demand higher spreads. An increase in uncertainty likewise decreases the expected returns given concave payoff functions from defaultable lending. Both pessimistic shocks and uncertainty lead to higher spreads, and so the firm's investment is likewise reduced in response to it facing a higher cost of financing. However, both responses are muted relative to a world with full information, and so the endogenous negative covariance between default and recovery rates arises, one that is well established in finance.[1] These responses to information are persistent, as learning is slow and gradual. Thus, the *information spreads* concept has a double meaning. Credit spreads respond to information, and information itself spreads through the economy, but only slowly, and signals have persistent impacts.

We evaluate this mechanism empirically using aggregate and firm-level data on bond spreads. Bond spreads capture the cost of the firm raising financing directly through debt, or the shadow cost for those firms not actively issuing new debt. At the aggregate level, our signal for new publicly available information is the mean and variance of current revisions in professional forecasters' expectations of quarter-ahead corporate profits. We show that these revisions strongly predict excess corporate bond spreads at long horizons. Specifically, we measure expectations of next quarter corporate profits

[1] An academic example is Acharya et al. (2007), while an example from industry is Hamilton et al. (2007).

over a long time series of about 150 quarters between 1970 and 2010 from the Survey of Professional Forecasters (SPF), which is the oldest survey of macro forecasts in the US and is closely watched by market participants. Current revisions in the SPF consensus forecast of next quarter profits are strongly negatively correlated over up to 2 years horizons with a variety of measures of corporate bond spreads in the corporate bond market, after controlling for realized outcomes including corporate profits. Moreover, on the real side, our survey-based measure has significant forecasting power for various standard economic aggregates, including business investment and GDP and employment growth. Again, the predictability of real aggregates is consistent with the model and follows from the predictability of interest rate spreads.

A sound micro-founded theory of credit spreads should not only be consistent with aggregate patterns, but it should explain patterns at the firm level as well. We therefore turn to microdata on firm-level earnings forecasts from the Institutional Brokers' Estimate System (IBES), as well as bond spreads and investment from standard sources. First, we use the microdata to confirm that the predictability results hold also at the firm-level. A firm-level measure of short-term quarterly analyst forecast revisions between 1982 and 2010 from IBES is strongly and economically related to spreads and investment over long horizons. Second, while we recognize that it is challenging, we take an important step toward establishing causality. Namely, we construct measures of exogenous changes or "shocks" to investors' forecasts of future firm profitability. The idea of these additional finer tests is to capture variation in the forecasts that is plausibly unrelated to *current* macroeconomic and firm conditions and, as such, less likely to be due to alternative forces or reverse causality. We utilize two approaches to construct these exogenous "noise shocks", one based on analyst-specific variation similar to Fracassi, Petry, and Tate (2016) and another based on brokerage-house mergers similar to Hong and Kacperczyk (2010).

The micro evidence further strengthens support for our "information" spreads, in which agents are only partially informed and through imperfect signals. Intuitively, if debt investors have full information about realized profits, they can perfectly identify the informational content from the noise term, and the return predictability from forecast revisions would disappear after controlling for the full information set. And controlling for the full state is unnecessary with our "noise shocks" approach, since these shocks are plausibly orthogonal to true information. With imperfect information, investors are likely to learn about corporate profits from publicly available data (such as the professional fore-

casts) to price forward-looking assets, which become predictable from forecast revisions. Plausibly exogenous sources of variation in forecasts in the microdata also help identify causality, distinguishing our story from alternative explanations that could lead to both worsening profit outlook and higher spreads at the aggregate level, such as deteriorating intermediary balance sheet conditions or reverse causality.

Returning to the theory, we assess the quantitative implications of our aggregate model both in terms of model fit and the importance of the theory of spreads for aggregate implications. For a realistic parametrization that is calibrated to match average investment, leverage, default rates, and the covariance of default and recovery rates, we show that the model successfully replicates the sign and magnitudes of the predictive regression results that we documented in the data. More importantly, the calibrated model can replicate two key stylized facts of the credit cycle more successfully than the full information benchmark, even with risk-neutral investors: (1) credit spreads on corporate bonds are larger than can be explained by empirically plausible defaults; (2) credit spreads and defaults are counter-cyclical. By contrast, credit spreads are much lower and counterfactually procyclical in the full information benchmark. The model also boosts the volatility of investment relative to the perfect information benchmark. Using the 2008-2009 financial crisis as an important example, the model generates a persistent widening in credit spreads which is up to three times larger than that predicted by full information. This is because during the crisis forecast revisions are noisier than during normal times, and more pessimistic than changes in firm fundamentals. The results of a quantitative counterfactual indicate that excessively pessimistic and noisier signals in 2008-2009 account for about half of the spike in spreads and one-fifth of the contraction in aggregate investment.

Finally, we use our simulated data to reconstruct the Gilchrist and Zakrajšek (2012) decomposition of spreads. Namely, using pooled cross-sectional and time-series variation in spreads, we regress spreads on the market-implied default probability. We then use this relationship to decompose the aggregate spread into the default-predicted component and the residual, which has been interpreted as an excess bond premium. Importantly, there is no true excess bond premium in our model: lenders are risk neutral and competitive bond prices rationally reflect all available information, and so every bond pays the risk-free rate in expectation. However, since the regression is linear in default probability, it does not allow for state-dependent variation in the severity of default, captured by recovery rates. The residual component in our model therefore reflects this state-dependent variation in recovery rates, and is highly predictive of future cycles. Our theory therefore

reinterprets this residual component, and the extent to which it can be interpreted as an excess bond premium.

Overall, our results indicate that imperfect information in credit markets is an important source of macroeconomic fragility. Furthermore, these results suggest that policies that promote financial stabilization by helping to anchor investors' expectations about firm creditworthiness, such as direct government subsidies to firms or Fed borrowing facilities, may have substantial benefits.

Related Literature We contribute to several literatures. First, our paper focuses on the link between credit markets and business cycles and is complementary to a large literature on the financial accelerator. Within this literature, we relate most closely to existing work on (corporate) bond spreads in macroeconomic models (e.g., Gilchrist, Sim, and Zakrajšek, 2014; Arellano, Bai, and Kehoe, 2019; Khan, Senga, and Thomas, 2014). This literature has generally modeled short-term debt using a full-information rational expectations approach.[2] This literature has struggled to simultaneously match spreads and default data, especially given reasonable costs of default.[3] Our modeling approach differs in subtle ways (e.g., long term debt), but our main contribution to this literature is to introduce a novel type of credit supply shock, driven by fluctuations in the mean and dispersion of these signals, which lead to changes in credit spreads. We show that the mechanism simultaneously explains the level and variation in spreads, with empirically plausible bond maturity, default, and recovery rates. Moreover, we do this with risk-neutral lenders, i.e., without requiring fluctuations in risk premia. We highlight the predictability of credit spreads, and their causal impact on the business cycle. Again, our approach reinterprets the evidence of excess bond premia as reflecting time varying recovery rates.

Our mechanism is distinct but complementary to those that have been previously identified in the literature on credit cycles, such as intermediary balance sheet constraints (e.g., Gertler and Karadi, 2011; Gertler and Kiyotaki, 2010; He and Krishnamurthy, 2013) and behavioral biases (Bordalo, Gennaioli, and Shleifer, 2018; Bordalo, Gennaioli, Shleifer,

[2] An older literature similarly assumed asymmetric information but with true costly state verification (e.g., Carlstrom and Fuerst, 1997; Bernanke, Gertler, and Gilchrist, 1999). Relative to this older literature, our firms solve dynamic problems where default is endogenous to their level of borrowing.

[3] Gomes and Schmid (2020) is an exception assuming Epstein-Zin preferences to generate large fluctuations in risk premia, and in turn, credit spreads.

and Terry, 2019; and Greenwood, Hanson, and Jin, 2019).[4] Empirically, our mechanism is tied to the measured pro-cyclical recovery rates under default. To give further empirical support to our independent and complementary channel, we show that even after controlling for changes in fundamentals, revisions and noise are significant in predicting future spreads at both the macro- and firm- levels. In testing the model implications, we also relate to the recent macro literature that uses micro data to examine the link between expectations and firm decisions (Coibion, Gorodnichenko, and Ropele, 2020; Coibion, Gorodnichenko, and Saten, 2018), and the micro evidence we contribute supports the recent empirical findings that credit spreads are tightly linked to future aggregate outcomes (Gilchrist and Zakrajšek, 2012; López-Salido, Stein, and Zakrajšek, 2017).

More broadly, our paper also speaks to a long and rich literature emphasizing the role of imperfect information in modern business cycle theory (e.g. Lucas, 1972; Woodford, 2003; Sims, 2003; Maćkowiak and Wiederholt, 2009; Collard, Dellas, and Smets, 2009; Lorenzoni, 2009). In our model, changes in expectations from public surveys can be interpreted as "news shocks" in credit markets. Moreover, these signals provide only a noisy forecast of the actual future profit, leaving a role for "noise shocks" in an incomplete-markets model. Empirically, the existence of noise helps us plausibly identify causation. On the theoretical side, in the existing literature, noise often dampens the impact of signals, but, in our model, noise itself has first-order impacts. To the best of our knowledge, our paper is the first to develop a model of credit spreads based on noisy learning.

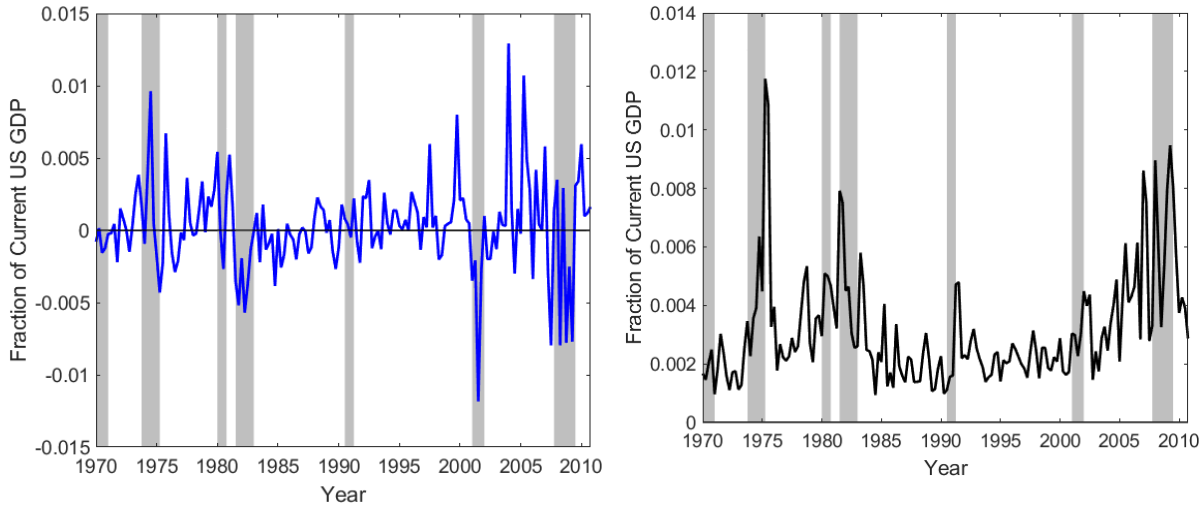
2 Empirical Evidence

This section presents empirical evidence on the role of imperfect information in credit markets. We start with evidence from aggregate data, which is more relevant to our macro simulations, and then present micro evidence, which serves as a further test of our mechanism and provides evidence on the causal relationship of the signals on spreads and real outcomes.

[4]We are closest to Bordalo, Gennaioli, Shleifer, and Terry (2019) and Krishnamurthy and Li (2025), in our emphasis on the role of expectations. Whereas we relax the "full information" of full information rational expectations, Bordalo et al. (2019) relax the "rational expectations" assumption, instead introducing diagnostic expectations as a source of credit cycles. Focusing on financial crises rather than credit spreads, Krishnamurthy and Li (2025) use imperfect information to understand financial crisis patterns. They show belief fluctuations are essential, and both Bayesian learning and diagnostic model can match crisis patterns.

Figure 1: Revisions in Investor Expectations of Corporate Profits

(a) Mean Revisions **(b)** Dispersion Across Forecasters



Note: This figure plots the current revision in next quarter's expected profit ($\text{rev}_t = \text{E}_t[\Pi_{t+1}] - \text{E}_{t-1}[\Pi_{t+1}]$) from the Survey of Professional Forecasters (SPF) as a fraction of current GDP. The left panel plots the mean level and the right panel shows the dispersion across individual forecasters. Shaded areas indicate NBER recession dates.

2.1 Aggregate Evidence

As our measure of publicly available signals of profitability, we use quarterly information on investor expectations of corporate profits from the Survey of Professional Forecasters (SPF). We construct our first explanatory variable of interest, Rev_t, as the current revision in investors' expectations of next quarter corporate profits: $\text{rev}_t = \text{E}_t\left[\Pi_{t+1}\right] - \text{E}_{t-1}\left[\Pi_{t+1}\right]$, i.e., it is the change between current and last period's investor expectations of next quarter corporate profits, and so it captures new information. The second explanatory variable of interest is the dispersion (standard deviation) of revisions across individual forecasters, denoted σ_t^{rev}. Figure 1 presents the quarterly aggregate data between 1973 and 2010.[5] Both revisions and their dispersion display considerable fluctuations around business-cycle turning points, with revisions dipping and their dispersion spiking markedly in downturns.

[5]Our baseline aggregate evidence is based on the 1970-2010 sample in order to be consistent with the sample period of the micro evidence, as there was a change in data provider from 2010 for the micro data. Nonetheless, the time-series correlations from aggregate data also holds in a longer sample covering more recent data (see Figure A.1) and Table A.3.

Table 1: Aggregate Evidence on Forecasting Credit Spreads

	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
rev_t	-0.103*	-0.186**	-0.129**	-0.124*	-0.057
[t]	[-1.68]	[-2.07]	[-2.04]	[-1.68]	[-1.47]
σ_t^{rev}	0.181*	0.307**	0.476**	0.471***	0.469***
[t]	[1.68]	[2.24]	[2.15]	[2.65]	[3.43]
N	148	147	146	145	141
R^2	0.39	0.61	0.60	0.55	0.56

Note: This table summarizes the results of time-series forecasting regressions of corporate bond spreads on investor expectations of corporate profits and its noise (see regression 1). t-statistics for k-period forecasting regressions are based on Newey-West (1987) standard errors, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

2.1.1 Expectations of Corporate Profits and Credit Spreads

First, we examine the time-series correlations between changes in investor expectations and subsequent risk premiums in the corporate bond market. In Table 1, we report estimates from the following multivariate forecasting regression:

$$\text{spr}_{t+k} = \alpha + \beta \text{rev}_t + \gamma \sigma_t^{\text{rev}} + \Gamma X_{t-1} + u_{t+k}, \tag{1}$$

where spr_{t+k} is the k-quarter ahead credit spread from Gilchrist and Zakrajšek (2012), with $k = 1,2,3,4,8$ respectively. The set of controls X_{t-1} include lagged corporate bond spreads and macroeconomic conditions (aggregate consumption, business investment, GDP, and corporate profitability (ROA)), excess stock returns, short and long rates (1-year Treasuries and the effective Fed Fund Rate), and the term spread. We compute the t-statistics for k-period forecasting regressions based on Newey and West (1987) standard errors.

To ease economic interpretation, both rev_t and σ_t^{rev} are re-scaled by their respective unconditional standard deviation. Thus, we can interpret the coefficients in Table 1 as the change in credit spread (in percentage point) associated with a one standard deviation revision in expectations Rev_t, or its noise σ_t. For instance, a one standard deviation upward revision in investors' expectations lowers the GZ spread by about 10 basis points in the following quarter, whereas a one standard deviation increase in the dispersion of

Table 2: Aggregate Evidence on Forecasting Investment and Output

	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
Output growth					
$\widehat{\text{spr}}_{t+1}$	-0.372	-0.561*	-0.650**	-0.691***	-0.625***
[t]	[-1.22]	[-1.95]	[-2.38]	[-2.69]	[-3.73]
N	148	147	146	145	141
R^2	0.317	0.572	0.508	0.460	0.337
Investment growth					
$\widehat{\text{spr}}_{t+1}$	-0.287	-0.512**	-0.619***	-0.819***	-1.02***
[t]	[-1.04]	[-2.29]	[-2.88]	[-3.67]	[-4.49]
N	148	147	146	145	141
R^2	0.562	0.567	0.570	0.543	0.569

Note: This table summarizes the results of time-series forecasting regressions of the cumulative output growth and business investment growth, in turn, on the component of credit spreads that is predictable (from regression 1) based on our measures of investor expectations (see regression 2). t-statistics for k-period forecasting regressions are based on Newey-West (1987) standard errors, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

revisions raises the spreads by about 18 basis points, which are respectively about 6 percent and 10 percent of the unconditional mean of spreads in our sample (1.6 percentage points).

2.1.2 Expectations of Corporate Profits and the Business Cycle

In Table 2, we show that our survey-based measure of changes in investor expectations of aggregate corporate profits has significant forecasting power for various standard economic aggregates, including GDP growth and business investment growth. To this end, we run multivariate time-series forecasting regressions of business cycle aggregates on the component of credit spreads that is predictable based on investor expectations of corporate profits from (1), controlling again for lagged corporate spreads and macroeconomic conditions, excess stock returns, short and long rates, and the term spread:

$$\Delta y_{t+k} = \alpha + \delta \widehat{\text{spr}}_{t+1} + \Gamma X_{t-1} + \varepsilon_{t+k}, \tag{2}$$

where Δy_{t+k} is, in turn, the k-quarter ahead cumulative investment and output growth, with $k = 1,2,3,4,8$ respectively.[6] $\widehat{\text{spr}}_{t+1}$ is the one-quarter ahead predicted spread from the forecasting regression (1) using both our measure of expectations of corporate profits rev_t and its dispersion σ_t^{rev}. As in the earlier regressions, we compute the t-statistics for k-period forecasting regressions based on Newey and West (1987) standard errors.

Table 2 shows that changes in expectations forecast real economic aggregates over up to 2-year horizons, and that the mechanism underlying the predictability of real aggregates is the predictability of credit spreads. For instance, a one standard deviation upward revision in investors' expectations today is associated with increases in investment and GDP growth of about 0.08 percentage points in the following year. Similarly, a one standard deviation increase in the dispersion of revisions today is associated with 0.15 percentage points lower business investment growth and GDP growth. These estimates in Table 2 confirm the finding of López-Salido, Stein, and Zakrajšek (2017) that credit spreads are a strong predictor of business cycle variables.

2.1.3 Economic Significance During the Financial Crisis

In summary, our aggregate evidence indicates that both deterioration in investor expectations of corporate profits and stronger disagreements about expectations tend to be followed by subsequent widening of credit spreads, and that the timing of this widening is, in turn, closely tied to the onset of a contraction in economic activity. To provide an alternative assessment of economic significance, we consider the 2006 to 2008 period, when revisions were revised downward by about half of a standard deviation (44%), on average, and the dispersion of revisions increased by about 3 standard deviations (see Appendix Table A.1). Our first-stage estimates in Table 1 imply that the combined effect of downward revisions and higher dispersion raised spreads by about 60 basis points ($0.103 \times 0.44 + 0.181 \times 3$), on average, in that period.

Moreover, the combined magnitudes of the first and second stage estimates suggest that the impact of changes in investor expectations is economically meaningful also on the real side. Considering again the 2006 to 2008 period, our estimates imply that the combined effect of downward revisions and higher dispersion lowered investment and output by approximately 50 basis points (-0.819×-0.103×-0.44-0.819×0.181×3), on an av-

[6] In Appendix Table A.4, we present additional results where Δy_{t+k} is the quarter-on-quarter growth rate for GDP and business investment, respectively.

erage quarterly basis, between 2006 and 2008.

2.2 Evidence from Microdata

Some caution is needed in drawing firm conclusions from the above evidence. The aggregate nature of the data masks differences in the composition of firms, both over time and in the cross section. For instance, we cannot distinguish firms which reduced investment and had negative revisions in profit during a recession, from firms that reduced investment but were perceived to remain profitable (i.e., without negative revisions). If the aggregate evidence were primarily driven by the second group of firms, that would imply a different mechanism driving the credit cycle from the one we are proposing in this paper. Moreover, both financial variables and forecasts are forward looking and so causation is hard to infer. To address these justified concerns, we present more direct support for our mechanism in this section, using micro datasets that combine firm-level estimates of earning forecasts produced by financial analysts and firm-level investment and financing data. We also consider attempts to isolate exogenous changes in forecasts to address the causation concern.

2.2.1 Data Description

We use microdata to investigate the impact of fluctuations in investor expectations for U.S. public firms between 1982 and 2010. Our data sources include the IBES Detail History File (unadjusted) for analyst-by-analyst Earnings Per Share (EPS) forecasts, ICE/IDC and the Warga database for bond-level spreads, and quarterly Compustat for firm balance sheet information.[7]

Using the detailed analyst-by-analyst forecasts, we calculate the firm-level consensus EPS forecast as the median of all analysts' forecasts for the relevant period. We then construct a quarterly measure of forecast revisions at the firm level that is analogous to our aggregate measure: $\text{rev}_{it} = \text{E}_t\left[\Pi_{i,t+1}\right] - \text{E}_{t-1}\left[\Pi_{i,t+1}\right]$, i.e., the firm-level measure is defined as the change between current and last period's forecasts of next quarter corporate profits of firm i at time t. Furthermore, we measure noise in investor expectations of corporate profits, σ_{it}^{rev}, as the dispersion (standard deviation) of revisions across individual

[7]We avoid using the off-the-shelf consensus forecast from the IBES Summary History File because it is known to be problematic due to backfilling and stale information among other issues (see, for example, Bouchaud, Kruger, Landier, and Thesmar, 2019).

forecasters at t.[8] As explained below, we also consider a residualized version of rev_{it}, which is constructed as the analyst-specific component that is estimated after controlling for the firm-specific component of rev_{it}. As in the aggregate data, we rescale the measures by their respective unconditional standard deviations to facilitate interpretation.

We then merge the firm-level measure of forecast revisions with monthly bond-level spreads from ICE/IDC for 1998-2010, which has comparable coverage to the formerly available Merrill Lynch database, and from the Warga database (via Mergent FISD) for 1982-1997. Finally, we merge the dataset with Compustat. Since the IBES information is available starting from 1982, the resulting sample is a panel of about 5,000 bonds and 700 firms between 1982 and 2010. Appendix Table A.2 presents the summary statistics for the main variables.

2.2.2 Cross-Sectional Correlations

We start by using panel regressions to confirm that the negative time-series relation between changes in expectations of corporate profits and credit spreads in the aggregate also holds in the cross-section of firms. To that end, we repeat our two-step regression approach, but now using the firm-level measures of expectations (denoted by rev_{it} and σ_{it}^{rev}), spread (spr_{it+k}) and investment growth (Δy_{t+k}), while controlling for firm-level lagged spread, firm size and profitability, and time fixed effects τ_t:

$$\text{spr}_{it+k} = \alpha + \beta \text{rev}_{it} + \gamma \sigma_{it}^{\text{rev}} + \Gamma X_{it-1} + \tau_t + u_{it+k}, \tag{3}$$

$$\Delta y_{it+k} = \alpha + \delta \widehat{\text{spr}}_{it+1} + \Gamma X_{it-1} + \tau_t + \varepsilon_{it+k}. \tag{4}$$

The results are reported in Panels A and B of Table 3, respectively.

2.2.3 Evidence from "Shocks" to Revisions Using Instruments

An important concern with both our time-series and baseline cross-sectional estimates is that they may erroneously pick up omitted macro variables, such as those related to other theories of the business cycle. For example, a contraction in bank lending may lead to higher spreads and, in turn, harm future profitability. Revisions are clearly an endogenous outcome that may be driven by these shocks. Moreover, revisions may be

[8] In instances when the same analyst issues multiple forecasts for the same firm in the same quarter, we keep only the first forecast issued.

Table 3: Cross-Sectional Correlations from Micro Data

Panel A: Expectations and Credit Spreads					
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
rev_{it}	-0.056***	-0.050***	-0.037***	-0.037***	0.024
[t]	[-8.17]	[-6.57]	[-4.31]	[-3.55]	[1.31]
σ_{it}^{rev}	0.036***	0.054***	0.067***	0.088***	0.127***
[t]	[5.48]	[6.43]	[6.20]	[6.34]	[5.90]
Time FE	Yes	Yes	Yes	Yes	Yes
N	119,808	112,331	101,962	92,453	64,311
Bonds	4,218	3,991	3,817	3,609	3,007
Panel B: Predicted Spreads and Firm Investment					
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
$\widehat{\text{rev}}_{it}$	-0.695**	-0.848***	-0.584**	-0.768***	0.629
[t]	[-2.17]	[-2.59]	[-2.10]	[-2.66]	[1.52]
Time FE	Yes	Yes	Yes	Yes	Yes
N	13,779	13,496	13,198	12,833	11,489
Firms	642	633	627	613	589

Note: This table summarizes the results of firm-level forecasting regressions of corporate bond spreads on investor expectations of corporate profits and its noise (Panel A, see regression 3), and of investment growth on the component of corporate bond spread that is predictable based on our measures of investor expectations (Panel B, see regression 4). t-statistics are based on standard errors that are clustered at the bond level to allow for within-bond serial correlation (Panel A), or at the firm level to allow for within-firm serial correlation (Panel B), with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

due to realized changes in firm fundamentals that are not controlled for. To address these issues, we explore two different instrumental variables to isolate changes or "shocks" to revisions that are unrelated to realized macroeconomic and firm fundamentals.

The first instrument is a measure of "shocks" to revisions based on analyst-specific change in expectations that are plausibly independent from realized changes in firm fundamentals. Similar to Fracassi, Petry, and Tate (2016), we construct the "shocks" in two steps. First, we estimate analyst-specific time effects for revisions across all firms at time t.[9] Second, we construct an instrument for the revisions, as the average of the analyst-time effects across the analysts who evaluated the firms, and we use this in reduced form regressions. This instrumented revision contains no firm-specific component other than the composition of the analysts at a point in time.

More concretely, the analyst-specific shocks are estimated using a regression-based decomposition method as the analyst-quarter effects in an analyst-level regression of quarterly revisions that also includes firm-quarter effects to control for (changes in) firm fundamentals. First, we estimate:

$$\text{rev}_{jit} = \alpha_{it} + \beta_{jt}\text{Analyst}_{jit} + \varepsilon_{jit}, \tag{5}$$

where rev_{jit} is the change in expectations for firm i in quarter t by analyst j. α_{it} is a firm-quarter fixed effect.[10] Analyst_{jit} includes the explanatory variables of interest: dummy variables for each analyst j that take the value 1 if the analyst covered firm i in quarter t, and zero otherwise.

Although the matching of analysts to firms is unlikely to be random – for example, analyst teams are often organized by sector – the interpretation of our results is not affected by this type of matching because we compare each analyst's revisions only with those of peers who make forecasts for the same firm in the same quarter. Then, we calculate the average of the resulting analyst-specific shocks within a given firm-quarter to construct

[9]One potential concern with this construction is that the analyst-time fixed effects may be picking up industry-time fixed effects if analysts were not randomly assigned. To this end, we conduct a robustness test where we use analyst fixed effects instead, and the results below remain robust (see Appendix A.7).

[10]This approach makes it unnecessary to include any time-varying controls for firm fundamentals such as size and profitability, since they cannot be identified independently from the fixed effects. It also mitigates selection concerns.

the firm-level shocks, $\varepsilon_{it}^{\text{rev}}$, i.e.

$$\varepsilon_{it}^{\text{rev}} = \frac{1}{N_{it}} \sum_{j} \widehat{\beta}_{jt} \text{Analyst}_{jit} \tag{6}$$

where N_{it} denotes the number of analysts for a given firm i and quarter t. The variation is therefore completely driven by the composition of analysts. The dispersion of these shocks, denoted by $\sigma_{it}^{\varepsilon^{\text{rev}}}$, are calculated in an analogous way, as the standard deviation of the analyst-specific shocks within a given-firm quarter.[11]

With our instruments $\text{IV}_{it} = \{\sigma_{it}^{\varepsilon^{\text{rev}}}, \varepsilon_{it}^{\text{rev}}\}$, we estimate the following regressions using two-stage least squares (2SLS):

$$\text{rev}_{it} = \zeta_0 + \zeta_1 \varepsilon_{it}^{\text{rev}} + \zeta_2 \sigma_{it}^{\varepsilon^{\text{rev}}} + \Gamma X_{it-1} + \tau_t + u_{it}, \tag{7}$$

$$\sigma_{it}^{\text{rev}} = \theta_0 + \theta_1 \varepsilon_{it}^{\text{rev}} + \theta_2 \sigma_{it}^{\varepsilon^{\text{rev}}} + \Gamma X_{it-1} + \tau_t + u_{it}, \tag{8}$$

$$\text{spr}_{it+k} = \alpha + \beta \widehat{\text{rev}}_{it} + \gamma \widehat{\sigma}_{it}^{\text{rev}} + \Gamma X_{it-1} + \tau_t + \varepsilon_{it+k}. \tag{9}$$

with $k = 1, 2, 3, 4, 8$ respectively. As before, firm-level controls include lagged spread, firm size and profitability, and τ_t denotes time fixed effects. The results are reported in Panel A of Table 4. The negative (positive) relation between changes in expectations of corporate profits (dispersion in forecasts) and corporate credit spreads continues to be significant. The magnitudes of coefficients are also comparable to the correlations reported in Panel A of Table 3.

In addition, we augment the instrument set IV_{it} with one more instrument that exploits variation in revisions around 15 brokerage house mergers between 1982 and 2005 that affect over 500 firms for which we have complete information on revisions. The source of variation here, as documented by Hong and Kacperczyk (2010), is that these mergers reduce competition and lead to an increase in optimism bias for firms covered by both merging houses before the merger – i.e., they have a positive effect on revisions, which is plausibly unrelated to realized firm and macroeconomic fundamentals. Specifically, we use a dummy variable merger_{it} that is equal to one if a firm i was covered by

[11] In our setting, the main threat to identification is selection – e.g. if optimistic analysts sort into more profitable firms. To alleviate this concern, we conduct a "placebo test" to see whether our analyst instrument for revisions is correlated with *past* firm profits. If optimistic analysts sort into better performing firms, then we would expect a positive correlation between past profits and our analyst-based instrument. As shown in Table A.8, we do not find any significant correlations.

Table 4: Impact of "Shocks" to Revisions on Credit Spreads Using IV

Panel A: $\text{IV}_{it} = \varepsilon_{it}^{\text{rev}}, \sigma_{it}^{\varepsilon^{\text{rev}}}$					
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
$\widehat{\text{rev}}_{it}$	-0.092**	-0.113**	-0.043	-0.023	-0.275***
[t]	[-2.13]	[-2.32]	[-0.84]	[-0.38]	[-3.92]
$\widehat{\sigma}_{it}^{\text{rev}}$	0.048**	0.065***	0.096***	0.115***	0.114***
[t]	[2.34]	[2.68]	[3.50]	[3.67]	[2.86]
Time FE	Yes	Yes	Yes	Yes	Yes
N	118,888	111,510	101,194	91,754	63,832
Bonds	4,203	3,979	3,785	3,597	2,996
Panel B: $\text{IV}_{it} = \sigma_{it}^{\varepsilon^{\text{rev}}}, \varepsilon_{it}^{\text{rev}}, \text{merger}_{it}$					
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
$\widehat{\text{rev}}_{it}$	-0.104**	-0.117**	-0.048	-0.013	-0.203***
[t]	[-2.39]	[-2.40]	[-0.93]	[-0.21]	[-2.80]
$\widehat{\sigma}_{it}^{\text{rev}}$	0.043**	0.063***	0.094***	0.119***	0.140***
[t]	[2.13]	[2.60]	[3.44]	[3.79]	[3.49]
Time FE	Yes	Yes	Yes	Yes	Yes
N	118,888	111,510	101,194	91,754	63,832
Bonds	4,203	3,979	3,785	3,597	2,996

Note: This table summarizes the firm-level evidence using two-stage least squares with instrumental variables (see regressions 7-9). In Panel A, the instruments are residualized rev_{it}, $\varepsilon_{it}^{\text{rev}}$, and its noise, $\sigma_{it}^{\varepsilon^{\text{rev}}}$. In Panel B, we use brokerage house mergers as an additional instrument. t-statistics are based on standard errors that are clustered at the bond level to allow for within-bond serial correlation, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

two brokerage houses that merged before t, and zero otherwise. In Panel B of Table 4, we report the results from 2SLS using both merger_{it} as an additional instrument.

The estimates for spreads remain statistically significant and stable under both approaches. Such evidence helps to distinguish our mechanism from other macro theories because it shows that changes in expectations matter for spreads and investment even after we control for aggregate shocks by including time effects and for realized changes in firm fundamentals. Furthermore, the evidence also helps to distinguish our mechanism from behavioral theories of the credit cycle that emphasize diagnostic expectations (e.g., Bordalo, Gennaioli, and Shleifer, 2018). In these theories, though changes in expectations amplify the cycle, the ultimate driving forces of the cycle remain realized changes in fundamentals. As such, the evidence that even after controlling for changes in fundamentals there is an independent role for expectations, indicates that learning and behavioral biases are distinct and complementary mechanisms.

2.2.4 Additional Supporting Evidence

Credit Spread Decomposition The literature's analysis of bond spreads has emphasized important roles for default concerns but also the "excess bond premium" (EBP), a default-risk factor that captures compensation demanded by investors—above and beyond expected losses—for bearing exposure to corporate credit risk (e.g., Gilchrist and Zakrajšek, 2012). We show that our information spread theory has important explanatory power for both components.

We construct the two components of credit spreads – default and EBP – following the methodology in Gilchrist and Zakrajšek (2012),[12] and re-run our regressions separately on both components. Table 5 report results from the panel regression (3), and for robustness, we also repeat the IV regression (9) on both spread components (see Appendix Table A.9). The key takeaway from these results is that our information proxies are important for both the default component and the EBP; in other words, revisions and their dispersions affect not only expected credit losses, but also the required compensation of investors for any given expected losses. We later show that this also holds in the model.

[12]Specifically, we run corporate bond spreads on the Merton-based distance-to-default (see equation 8 in Gilchrist and Zakrajšek, 2012) and seven bond-level controls (following Gilchrist and Zakrajšek (2012) Section 3B: bond duration, amount outstanding, coupon rate, age of the issue, indicator for callable, and fixed effects for 3-digit NAICS and S&P credit ratings).

Table 5: Credit Spread Decomposition

Panel A: spr_{it+k} = excess bond premium (EBP)					
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
rev_{it}	-0.043***	-0.043***	-0.030***	-0.037***	0.021
[t]	[-6.11]	[-5.61]	[-3.52]	[-3.44]	[1.13]
σ_{it}^{rev}	0.011*	0.020**	0.033***	0.051***	0.108***
[t]	[1.70]	[2.55]	[3.13]	[3.71]	[5.00]
Time FE	Yes	Yes	Yes	Yes	Yes
N	97,524	91,930	83,298	75,427	52,643
Bonds	3,406	3,245	3,131	2,965	2,489
Panel B: spr_{it+k} = default component					
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
rev_{it}	-0.014***	-0.011***	-0.010***	-0.001	0.004
[t]	[-7.86]	[-4.75]	[-3.36]	[-0.47]	[0.81]
σ_{it}^{rev}	0.018***	0.027***	0.036***	0.044***	0.047***
[t]	[9.25]	[10.01]	[9.66]	[9.67]	[7.13]
Time FE	Yes	Yes	Yes	Yes	Yes
N	97,524	91,930	83,298	75,427	52,643
Bonds	3,406	3,245	3,131	2,965	2,489

Note: This table summarizes the results of firm-level forecasting regressions of different components of corporate bond spreads on investor expectations of corporate profits and its noise. We follow the procedure in Gilchrist and Zakrajšek (2012) to decompose the corporate bond spread into the excess bond premium (Panel A) and the default component (Panel B), and then run regression 3 on each component. t-statistics are based on standard errors that are clustered at the bond level to allow for within-bond serial correlation, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Uncertainty or Disagreement? The dispersion of revisions across individual forecasters, σ_t^{rev}, could reflect either the degree of disagreement among forecasters (due to their potentially different private signals, for example) or the level of uncertainty (or precision) of their forecasts. While disentangling the two channels from the data is beyond the scope of the paper, the model we build in the next section examines how the uncertainty of forecasts affects credit and business cycles. Thus, we provide further corroborating evidence for this channel using forecast errors. Since forecast errors capture the ex-post idiosyncratic forecast accuracy, they are a better measure of uncertainty or precision of forecasts than disagreement. Specifically, we replace rev_t and σ_t^{rev} by forecast errors (consensus forecast minus realized profit) and the dispersion of it, respectively, in both the aggregate regression (1) and the firm-level regression (3). As shown in Table A.10, these proxies remain highly significant for forecasting credit spreads both in the aggregate and at the firm level.

3 Model

3.1 Economic Environment

A. Agents, Technology, and Income Processes

Time is discrete and the horizon infinite. There are continua of firms and perfectly competitive lenders. To focus solely and squarely on the imperfect information channel, we assume that both agents are risk-neutral and fully rational.

A firm j produces output y_{jt} using capital k_{jt} according to the technology:

$$y_{jt} = A_{jt} k_{jt}^{\alpha}, \tag{10}$$

where $\alpha < 1$, and $a_{jt} = \log A_{jt}$. Productivity has an aggregate component z_t that is persistent, and an idiosyncratic component η_{jt} that is i.i.d. over time and across firms:

$$a_{jt} = \overline{a} + z_t + \eta_{jt}, \tag{11}$$

where $\eta_{jt} \sim iid\ N(\mu_\eta, \sigma_\eta^2)$. z_t is an aggregate shock that approximates the following autoregressive processes:

$$z_t = \rho_z z_{t-1} + \varepsilon_t^z, \tag{12}$$

with $\varepsilon_t^z \sim iid\ N(0,\sigma_\varepsilon^2)$. Each firm pays a fixed operating cost f. Hence a firm's operating profit before tax in each period is:

$$\pi_{jt} = A_{jt}k_t^\alpha - f. \tag{13}$$

Capital accumulation follows:

$$k_{jt+1} = (1-\delta)k_{jt} + i_{jt}, \tag{14}$$

where i_{jt} is the current investment and δ is the rate of depreciation.

B. Information Frictions

Agents cannot distinguish z_t from η_{jt} in a_{jt}. Instead, they receive a noisy public signal s_t related to the contemporaneous component ε_t^z of the aggregate productivity process (Lorenzoni, 2009):

$$s_t = \varepsilon_t^z + u_t, \tag{15}$$

where u_t denotes the noise in the signal, which prevents agents from perfectly identifying the aggregate shock ε_t^z. Moreover, u_t is i.i.d. normal and has a time-varying noise σ_{ut}^2 that is i.i.d. and truncated normal with mean μ_{σ_u} and variance $\omega_{\sigma_u}^2$. ε_t^z, η_{jt}, u_t and σ_{ut} are mutually uncorrelated. Let

$$\Omega_{jt} = \left\{a_{jt}, s_t, \sigma_{ut}, a_{jt-1}, s_{t-1}, \sigma_{ut-1}, ..., a_{j0}, s_0, \sigma_{u0}\right\} \tag{16}$$

denote the time-t history of signals and noise up to t. In sum, the time-t information set of a firm j's potential lenders includes the structure of the economy and all parameters, the history of all the model variables through time t, except the past and current realizations of the shocks $\{\varepsilon_t^z, \eta_{jt}\}$, and the history Ω_{jt}.

C. Financial Frictions

To finance investment projects, a firm can use internal funds and issue long-term debt. Let b_{jt} denote the stock of outstanding liabilities at time t and q_{jt} the per unit market price of these liabilities. The firm is required to pay back a fraction λ of the principal in every period, while the remaining $(1-\lambda)$ remains outstanding, which implies that the debt has

an expected life of $\frac{1}{\lambda}$. In addition to principal amortization, the firm is also required to pay a periodic coupon c per unit of outstanding debt in every period.

Investors buy corporate debt at the market price q_{jt}, and collect coupon and principal payments, $(c+\lambda)b_{jt+1}$, until the firm defaults. We follow the default rule in Arellano, Bai, and Kehoe (2019), namely, firms default if equity payouts become negative. To derive the default condition, let $M(b_{jt},\Omega_{jt})$ denote the net borrowing limit, i.e. the maximum amount of new debt a firm can raise, given the current bond price schedule (defined below), $q(b_{jt+1},k_{jt+1},\Omega_{jt})$, net of investment expenses:

$$M(b_{jt},\Omega_{jt}) = \max_{b_{jt+1},k_{jt+1}} q(b_{jt+1},k_{jt+1},\Omega_{jt})\Big(b_{jt+1}-(1-\lambda)b_{jt}\Big) - k_{jt+1} \tag{17}$$

Firms pay their equity holders their revenues net of production costs, investment, tax and debt payments, and face a non-negative payout condition:

$$\begin{aligned} e_{jt} &\equiv e(z_t,\eta_{jt},k_{jt},b_{jt},k_{jt+1},b_{jt+1},\Omega_{jt}) \\ &= \underbrace{(1-\tau)\big(\exp(z_t+\eta_{jt})k_{jt}^{\alpha}-f\big)}_{\text{after-tax profit}} - \underbrace{(c+\lambda)b_{jt}}_{\text{debt repayment}} + \underbrace{q(b_{jt+1},k_{jt+1},\Omega_{jt})\Big(b_{jt+1}-(1-\lambda)b_{jt}\Big)}_{\text{new debt issues}} \\ &\quad - \underbrace{\big(k_{jt+1}-(1-\delta)k_{jt}\big)+\tau\big(\delta k_{jt}+cb_{jt}\big)}_{\text{investment and tax rebate}} \geq 0, \end{aligned} \tag{18}$$

where τ is the firm's effective tax rate. This expression for equity distributions is consistent with the fact that interest payments are tax deductible.

From (17) and (18), one can define the cutoff level of the idiosyncratic shock $\eta^*_{jt+1} = \eta^*(k_{jt+1},b_{jt+1},z_{t+1},\Omega_{jt+1})$, which satisfies:

$$\begin{aligned} (1-\tau)\big(\exp(z_{t+1}+\eta^*_{jt+1})k^{\alpha}_{jt+1}-f\big) - \big(c+\lambda\big)b_{jt+1} + (1-\delta)k_{jt+1} \\ + \tau(\delta k_{jt+1}+cb_{jt+1}) + M(b_{jt+1},\Omega_{jt+1}) = 0 \end{aligned}$$

The default condition in $t+1$ has a cutoff form: repay in $t+1$ if $\eta_{jt+1} \geq \eta^*_{jt+1}$, and default otherwise.

3.2 Firm's Problem

Now we formalize firm j's problem recursively. First, we define a composite state variable, namely a firm j's net profit in period t:

$$\begin{aligned} x_{jt} &= x\big(z_t, \eta_{jt}, b_{jt}, k_{jt}\big) \\ &= (1-\tau)\big(\exp(z_t+\eta_{jt})k_{jt}^{\alpha} - f\big) - (c+\lambda)b_{jt} + (1-\delta)k_{jt} + \tau(\delta k_{jt} + c b_{jt}). \end{aligned} \tag{19}$$

Let $V(b_{jt}, x_{jt}, \Omega_{jt})$ denote the value of firm j after all shocks are realized in period t. For the equity owner, the value of a defaulting firm is

$$V(b_{jt}, x_{jt}, \Omega_{jt}) = 0, \tag{20}$$

i.e. if it cannot satisfy the nonnegative equity payout condition (18). Non-defaulting firms choose new capital k_{t+1}, debt b_{jt+1}, and equity payouts e_{jt} to solve:

$$V(b_{jt}, x_{jt}, \Omega_{jt}) = \max_{b_{jt+1}, k_{jt+1}, e_{jt}} \left\{ e_{jt} + \beta \left[\iiiint_{\eta_{jt+1} \geq \eta^*(k_{jt+1}, b_{jt+1}, z_{t+1}, \Omega_{jt+1})} \right. \right. \tag{21}$$

$$\left. \left. V\Big(b_{jt+1}, x\big(z_{t+1}, \eta_{jt+1}, b_{jt+1}, k_{jt+1}\big), \Omega_{jt+1}\Big) d\Phi(\eta_{jt+1}) d\widetilde{F}(z_{t+1}|\Omega_{jt}) dG(s_{t+1}|\sigma_{ut+1}) dH(\sigma_{ut+1}) \right] \right\}$$

subject to non-negative debt,

$$b_{jt+1} \geq (1-\lambda) b_{jt} \tag{22}$$

and the nonnegative equity payout condition (18). $\widetilde{F}(z_{t+1}|\Omega_{jt})$ indicates the perceived distribution of z_{t+1} conditional on the information set Ω_{jt}. This does not necessarily reflect the true distribution conditional on z_t, $F(z_{t+1}|z_t)$. Agents continuously update their perceived distribution, as new information arrives in each period.

3.3 Debt Market Equilibrium

The bond pricing schedule ensures that lenders break even in expectation:

$$
\begin{aligned}
q(b_{jt+1},k_{jt+1},\Omega_{jt}) = \beta \times \Bigg[& \iiint \Big(1-\Phi\big(\eta^*(z_{t+1},k_{jt+1},b_{jt+1},\Omega_{jt+1})\big)\Big) \\
& \times \underbrace{\Big[c+\lambda+(1-\lambda)q\big(b_{jt+2},k_{jt+2},\Omega_{jt+1}\big)\Big]}_{\text{no default payoff}} d\widetilde{F}(z_{t+1}|\Omega_{jt}) dG(s_{jt+1}|\sigma_{ut+1}) dH(\sigma_{ut+1}) \\
& + \iiiint_{\eta_{jt+1}<\eta^*(z_{t+1},k_{jt+1},b_{jt+1},\Omega_{jt+1})} \underbrace{B(b_{jt+1},k_{jt+1},\eta_{jt+1},z_{t+1},\Omega_{jt+1})}_{\text{default payoff}} \\
& \times d\Phi(\eta_{jt+1}) d\widetilde{F}(z_{t+1}|\Omega_{jt}) dG(s_{jt+1}|\sigma_{jt}) dH(\sigma_{jt+1}) \Bigg]
\end{aligned} \tag{23}
$$

where b_{jt+2} and k_{jt+2} are consistent with the firm's policy functions:

$$
\begin{aligned}
b_{jt+2} &= g_b\Big(b_{jt+1}, x\big(z_{t+1},\eta_{jt+1},b_{jt+1},k_{jt+1}\big),\Omega_{jt+1}\Big), \\
k_{jt+2} &= g_k\Big(b_{jt+1}, x\big(z_{t+1},\eta_{jt+1},b_{jt+1},k_{jt+1}\big),\Omega_{jt+1}\Big).
\end{aligned}
$$

If default happens, creditors become (temporary) owners of the firm and the original equity owner receives zero payoff from the equity value. Creditors restructure the defaulted firm, and the cost of restructuring is $\xi \in (0,1]$ of the firm's undepreciated capital, $(1-\delta)k_{jt+1}$ (Townsend, 1979). After restructuring, creditors sell off the firm to new owners in the same period, and the firm resumes operating with capital $(1-\xi)(1-\delta)k_{jt+1}$ and zero debt. Thus, the bond recovery rate is given by:

$$
\begin{aligned}
& B(b_{jt+1},k_{jt+1},\eta_{jt+1},z_{t+1},\Omega_{jt+1}) \\
& \qquad = V\Big(0, x\big(z_{t+1},\eta_{jt+1},0,(1-\xi)(1-\delta)k_{jt+1}\big),\Omega_{jt+1}\Big)\frac{1}{b_{jt+1}}.
\end{aligned} \tag{24}
$$

We normalize the price of default-free bond to 1 by setting the coupon rate to $c = \frac{1}{\beta} - 1$. Credit spread is defined as the yield difference between defaultable and default-free debt with otherwise identical characteristics (e.g. maturity and coupon rate):

$$
\mathrm{spr}(b_{jt+1},k_{jt+1},\Omega_{jt}) = \frac{c+\lambda+(1-\lambda)\widetilde{\mathrm{E}}[q(b_{jt+2},k_{jt+2},\Omega_{jt+1})|\Omega_{jt}]}{q(b_{jt+1},k_{jt+1},\Omega_{jt})} - (c+1), \tag{25}
$$

where $\widetilde{\mathrm{E}}[\cdot]$ denotes the subjective expectations conditional on the observables.

4 Quantitative Analysis

In this section, we first describe our numerical approach, followed by a discussion of the calibration, and a comparison of moments in the model and the data.

4.1 Algorithm

We solve the model by simultaneously iterating on the debt pricing equation and the firm's value function, since bond prices depend on the firm's decision rules for (b_{jt+1}, k_{jt+1}). It is worth highlighting the key features that are unique to our imperfect information setting. Both the value function (21) and the bond pricing schedule (23) requires computing the conditional density function $\tilde{f}(z_{t+1}|\Omega_{jt})$, where Ω_{jt} denotes the history of signals (16), an infinite-dimensional object.

We solve the model by first recasting agents' information into a low-dimensional belief state and then applying standard dynamic programming techniques on a discretized state space. Specifically, given a history Ω_{jt}, agents use a Kalman filter to form posterior beliefs about the latent aggregate shock.[13] This filtering problem delivers the posterior mean $z_{jt|t}$ and the associated forecast variance $\Theta_{jt+1|t}$, which constitute sufficient statistics for computing expectations:

$$z_{t+1} \mid \Omega_{jt} \sim \mathcal{N}(\rho z_{jt|t}, \Theta_{t+1|t}). \tag{26}$$

As a result, we can reduce the dimensionality of the firm's problem: instead of tracking the entire information set Ω_{jt}, firms condition only on current balance sheet variables and beliefs about the aggregate state, $(b_{jt}, x_{jt}, z_{jt|t}, \Theta_{t+1|t})$. This approach preserves the key informational dynamics implied by the filtering problem while maintaining computational tractability.

We discretize both the posterior mean $z_{jt|t}$ and its associated variance $\Theta_{t+1|t}$. The conditional distribution of next period's beliefs is then represented by transition matrices defined over this discretized grid. Consistent with the simulated data, we treat the posterior mean $z_{jt|t}$ as a Markov state variable in the discretized model, while the forecast variance

[13] See Appendix B for the state-space model. We solve the Kalman filtering problem independently of the firm's dynamic programming problem, and use the implied belief dynamics to discipline the structural model (see Guvenen, 2007 for a related approach).

$\Theta_{t+1|t}$ is independently and identically distributed across time. Appendix C outlines the discretized firm problem.

4.2 Parameterization

Before jointly solving the firm's recursive problem and the debt market equilibrium, we first run a Kalman filter with time-varying noise σ_{ut} on simulated data (of N firms), given parameter values for $\{\rho_z, \sigma_\varepsilon, \overline{a}, \sigma_\eta, \mu_{\sigma_u}, \omega_{\sigma_u}\}$. Then, using the sample, we approximate $\widehat{z}_{jt|t}$ (see equation 26) as an AR(1) with persistence $\widehat{\rho}_z$ and standard error $\widehat{\varepsilon}_t^z \sim N(0, \sigma_{\widehat{\varepsilon}}^2)$, and $\Theta_{t+1|t}$ as i.i.d. normal with mean Θ and standard deviation σ_Θ. We then discretize $\widehat{z}_{jt|t}$ and $\Theta_{t+1|t}$, and solve the discretized firm problem in Appendix C. As a result, we have in total 18 parameters:

$$\{\alpha, \delta, \beta, \tau, c, \lambda, \rho_z, \sigma_\varepsilon, \mu_{\sigma_u}, \widehat{\rho}_z, \sigma_{\widehat{\varepsilon}}, \Theta, \sigma_\Theta, \overline{a}, \xi, \sigma_\eta, f, \omega_{\sigma_u}\}.$$

We calibrate the model at quarterly frequency and the sample period is from 1985Q1 to 2010Q4. We use data on U.S. public firms from Compustat, aggregate survey data from the Survey of Professional Forecasters, and data on U.S. corporate bonds from Moody's Default and Recovery Database (DRD) and Mergent Fixed Income Securities Database (FISD). We apply a combination of external and internal moments to calibrate model parameters. Specifically, we directly set parameter values for those with standard values in the literature, or according to their natural data counterpart. Then we jointly calibrate the rest of parameters to target firm-level moments.

The externally calibrated parameters are: $\{\alpha, \delta, \beta, \tau, c, \lambda, \rho_z, \sigma_\varepsilon, \mu_{\sigma_u}, \widehat{\rho}_z, \sigma_{\widehat{\varepsilon}}, \Theta, \sigma_\Theta\}$. The first four parameters take the common values in the literature, for returns to scale, depreciation rate, discount rate, and tax rate, respectively. The returns to scale parameter is 0.65, which is within the range of values used in the literature (e.g. Hennessy and Whited, 2007).[14] The quarterly depreciation rate δ is 0.025. The rate of time preference $\beta = 0.99$ implies an annualized risk-free rate of 4%. The effective corporate tax rate τ is 30%, in line with the evidence in Graham (2000). The next parameter is the periodic coupon rate

[14] We abstract from labor in the model, but choose a return to scale parameter that reflects endogenous labor response. Specifically, our returns to scale value (0.65) is intermediate between the elasticity with respect to capital alone (around 0.3) and aggregate returns to scale (around 0.8, e.g. Buera, Kaboski, and Shin, 2011). The former would be relevant for a firm with fixed labor, while the latter is relevant if labor were perfectly elastically supplied. Our intermediate level would therefore capture an upward-sloping labor supply.

c. We set it equal to $\frac{1}{\beta} - 1$, so that the price of default-free debt is one.

The next three parameters $\{\lambda, \rho_z, \sigma_\varepsilon\}$ are calibrated according to their natural data counterpart. We set λ equal to 0.05 per quarter, implying an average expected maturity of five years. This corresponds to the mean maturity of public bonds issued in the U.S. based on the FISD data. The next two parameters, ρ_z and σ_ε, govern the dynamics of firms' revenues, and we fit an AR(1) to the data on sales-to-asset from the quarterly Compustat database.

The next five parameters $\{\mu_{\sigma_u}, \widehat{\rho}_z, \sigma_{\widehat{\varepsilon}}, \Theta, \sigma_\Theta\}$ are related to the Kalman filter. We use the current revision in professional forecasters' expectations of quarter-ahead corporate profits as our empirical proxy for the signal s_t, which contains new information about the aggregate fundamental ε_t^z in each period plus some noise u_t (see equation 15). We scale the revisions by total non-financial assets of U.S. non-financial corporate businesses, and compute the dispersion across forecasters in each quarter as the time-varying noise, σ_{ut}. The mean of this series is used to calibrate μ_{σ_u}. After obtaining a sample of $\widehat{z}_{jt|t}$ and $\Omega_{t+1|t}$ from the Kalman filter, we use it to estimate $\{\widehat{\rho}_z, \sigma_{\widehat{\varepsilon}}, \Theta, \sigma_\Theta\}$, which we then use to calibrate the structural firm model.

The last five parameters $\{\overline{a}, \xi, \sigma_\eta, f, \omega_{\sigma_u}\}$ are jointly calibrated to target firm-level moments, which are the mean profit-to-asset ratio, the mean investment rate, the mean leverage, and the mean and standard deviation of default rate. The mean default rate is chosen to match Moody's value-implied average default rate per quarter, measured by the value of corporate bonds defaulted to the total value of outstanding bonds. The mean profitability, investment, and leverage are constructed using data from Compustat for the sample period. Since our model is highly nonlinear, all parameters affect all the moments. Nonetheless, some parameters are more important for certain statistics. The mean profit-to-asset is largely affected by the mean productivity $\overline{a}$. The mean leverage is affected by the bankruptcy cost ξ. The mean and standard deviation of default rate are jointly affected by the fixed cost f and the standard deviation of the idiosyncratic TFP, σ_η. The standard deviation of the time-varying noise, ω_{σ_u}, affects the mean investment rate. Table 6 reports the parameters in the baseline model.

4.3 Aggregate Implications

Tables 8 summarizes the model predictions of untargeted moments. We also consider two counterfactual models, in order to highlight the role of the time-varying noise and

Table 6: Parameterization

Parameter	Description	Model
Preferences and technology		
α	Returns to scale	0.65
δ	Depreciation rate	0.025
β	Time preference	0.99
$\bar{a}$	Mean productivity	-0.156
σ_η	Idiosyncratic shock (volatility)	0.0105
ρ_z	Aggregate shock persistence	0.93
σ_ε	Aggregate shock volatility	0.0073
f	Fixed cost	0.3027
External financing		
τ	Corporate tax rate	0.3
ξ	Bankrupty cost	0.34
c	Coupon rate	0.0101
λ	Debt amortization rate	0.05
Information frictions		
μ_{σ_u}	Mean noise	0.006243
ω_{σ_u}	Noise volatility	0.00814
$\widehat{\rho}_z$	Persistence of conditional mean	0.9278
$\sigma_{\widehat{\epsilon}}$	Std error of conditional mean	0.0075
Θ	Mean conditional variance	0.0085
σ_Θ	Std dev of conditional variance	0.0031

Table 7: Targeted Moments

	Data	**Baseline**	**Constant** σ_u	**Full Info**
	(1)	(2)	(3)	(4)
Profitability (mean)	0.223	0.213	0.214	0.235
Investment (mean)	0.021	0.027	0.027	0.024
Leverage (mean)	0.267	0.290	0.296	0.275
Default rate (mean)	0.013	0.015	0.014	0.015
Default rate (std)	0.012	0.010	–	–

imperfect information. In the first counterfactual, we assume that σ_{ut} is constant; in the second counterfactual, we solve a full information rational expectations model. To give each model the best shot, we separately calibrate each model to target similar moments. Columns (3) and (4) of Table 7 report the targeted moments in the counterfactual models.[15]

The comparison highlights the central role of imperfect information as well as of time-varying noise in generating realistic credit cycle dynamics. The baseline model – featuring imperfect information and time-varying noise – generates high and countercyclical credit spreads, even though investors are risk-neutral and fully rational. Investors price bonds based on perceived default probabilities inferred from noisy signals about future profitability. When signals deteriorate or become more dispersed, investors revise beliefs downward, but incompletely relative to the full-information benchmark. As a result, firms reduce borrowing and investment, but not enough. This muted response has two consequences: First, firms enter downturns with excessively high leverage relative to fundamentals. This raises default probabilities. Second, conditional on default, firms are in worse states—because balance sheets were not adjusted sufficiently in advance. This implies lower recovery rates in bad states. Together, these forces generate an endogenous negative covariance between default probabilities and recovery rates, which is a central implication of the model. Because bond prices depend on both default likelihood and recovery conditional on default, this covariance raises both the level and the volatility of credit spreads. Notably, this mechanism operates without any time-varying risk premia. Spreads are elevated because expected losses are state-dependent in a nonlinear way, not because investors require compensation for risk.

The comparison with the constant-noise counterfactual isolates the role of time-varying uncertainty. With constant noise, agents still face imperfect information, but the precision of signals does not vary over the cycle. As a result, belief updating is approximately time-invariant, and the degree of underreaction to fundamentals does not depend on macroeconomic conditions. In contrast, in the baseline model, noise is higher in downturns. This implies that agents learn more slowly in recessions; pessimistic signals are discounted more heavily, and as a result, firms deleverage too slowly when conditions worsen. This state-dependent learning friction amplifies financial fragility exactly in bad times. Firms remain highly leveraged in recessions, which increases the sensitivity of de-

[15]See Tables A.12 and A.13 in the appendix for the parameterization in the counterfactual models.

Table 8: Untargeted Moments

	Data	**Baseline**	**Constant** σ_u	**Full Info**
	(1)	(2)	(3)	(4)
Bond spread (mean)	0.019	0.010	0.005	0.004
Bond recovery (mean)	0.22	0.16	0.28	0.35
Leverage in default (mean)	0.41	0.48	0.29	0.24
σ(spread)	0.011	0.020	0.016	0.017
σ(invest)	0.067	0.061	0.043	0.055
σ(output)	0.015	0.019	0.010	0.011
σ(profit)	0.262	0.195	0.134	0.117
Corr(spread, invest)	-0.129	-0.102	-0.014	0.003
Corr(spread, profit)	-0.159	-0.145	-0.010	-0.003
Corr(spread, output)	-0.573	-0.155	-0.001	0.0285
Corr(spread, debt)	-0.036	-0.114	0.002	0.043
Corr(debt, output)	0.072	0.102	0.135	0.362
Corr(invest, output)	0.63	0.53	0.65	0.70
Corr(recovery, output)	0.65	0.47	0.26	0.21

fault outcomes to underlying shocks. Consequently, spreads become more volatile and more countercyclical.

In that environment, firms and investors perfectly observe fundamentals and therefore adjust borrowing and investment optimally in response to shocks. As a result, leverage is reduced promptly in downturns; firms enter default in less distressed states, and thus, recovery rates are higher and less state-dependent. Consequently, credit spreads are lower and insufficiently volatile, and fail to match the empirical patterns. This comparison highlights that the model's ability to generate realistic credit spreads does not come from standard channels such as risk premia or exogenous shocks to default, but rather from informational frictions that distort the joint dynamics of default and recovery.

The same mechanism has important implications for real activity. Because higher spreads raise the marginal cost of external finance, imperfect information does not only distort credit prices; it also distorts firms' financing and investment decisions. In the baseline model, bad or noisy signals lead investors to demand higher spreads, which in turn depresses firm borrowing and investment. Since learning is gradual, these financing conditions remain tight for longer, making the effects on real activity persistent. Quanti-

tatively, Table 8 shows that the baseline model produces substantially more volatile real aggregates than either counterfactual. Thus, time-varying noise does not simply raise the level of credit spreads; it strengthens the transmission of financial conditions to the real economy by making investment and output more sensitive to information-driven fluctuations in credit markets.

4.4 Model-Implied Regressions and Credit Cycles

We examine the extent to which our model generates credit cycles in two ways. To this end, we feed into the model the realized profitability shocks and signals (revisions and their dispersions) from the data, and conduct the following regressions. First, we repeat the forecasting regressions from Section (2.1) using the model-implied spread and the data series for rev_t and σ_t^{rev}; second, we repeat the Gilchrist and Zakrajšek (2012) regressions using our model-generated spreads.

Information Spreads To further evaluate the model fit, we examine whether the model can replicate the empirical relationship between information shocks – captured by revisions in expectations and their dispersion – and future credit spreads and real activity, while controlling for current financial conditions (current credit spreads). Table 9 reports the model-implied forecasting regressions that mirror the empirical specifications in Section 2.1, while Tables A.14 and A.15 present the corresponding results under full information and constant-noise counterfactuals.

The baseline model with imperfect information and time-varying noise successfully reproduces the key empirical patterns. Even after controlling for current spreads, positive revisions in expected profitability predict lower future spreads, while higher dispersion in revisions predicts higher spreads. This is a nontrivial result. Because current spreads already summarize market perceptions of default risk, controlling for them removes a large component of contemporaneous information about fundamentals. The fact that revisions and their dispersion still have predictive power implies that credit markets do not fully incorporate available information on impact.

This incomplete incorporation is precisely what the model delivers. Investors observe noisy signals and update beliefs gradually. As a result, revisions represent new information that is only partially impounded into prices at the time it arrives, and the dispersion of revisions captures time variation in signal precision, which affects how aggressively

Table 9: Model-Implied Regressions

	Forecasting Credit Spreads			
	Data		Model	
	1-qtr	2-qtr	1-qtr	2-qtr
rev_t	-0.103*	-0.186**	-0.021**	-0.013*
[t]	[-1.68]	[-2.07]	[-2.15]	[-1.70]
σ_t^{rev}	0.181*	0.307**	0.011**	0.005*
[t]	[1.68]	[2.24]	[1.82]	[1.68]
N	148	147	150	149
	Forecasting Investment			
	Data		Model	
	1-qtr	2-qtr	1-qtr	2-qtr
$\widehat{\text{spr}}_{t+1}$	-0.287	-0.512*	-0.033*	-0.014*
[t]	[-1.04]	[-2.29]	[-1.91]	[-1.76]
N	148	147	150	149

Note: The top panel summarizes the results of time-series forecasting regressions of corporate bond spreads on investor expectations of corporate profits and its noise (see regression 1), where the dependent variable is the average credit spread across firms over time, and we control for the current spread. The lower panel summarizes the results of forecasting aggregate investment using the component of corporate bond spread that is predictable based on our measures of investor expectations (see regression 2). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

agents update beliefs. Consequently, both the mean and variance of signals forecast future movements in spreads, even conditional on current spreads.

This feature is novel and central to the mechanism. In standard full-information environments, or more generally in settings where prices are sufficient statistics for fundamentals, controlling for current spreads would eliminate any additional predictive content of signals. Indeed, Table A.14 shows that under full information, revisions and their dispersion have essentially no predictive power for future spreads or investment once current conditions are taken into account. Similarly, under constant noise (Table A.15), revisions retain only limited predictive power and there is no role for the dispersion of signals.

In sum, credit spreads respond to information, but information is imperfect and gradually incorporated into prices. When signals are noisy – particularly in downturns – investors update cautiously, so prices underreact on impact. This generates predictable future adjustments in spreads as beliefs continue to evolve. At the same time, higher dispersion in signals reduces confidence and further slows learning, amplifying this delayed response.

These informational dynamics also explain the predictability of real activity. Because firms' investment decisions depend on financing costs, and because spreads adjust gradually to new information, information shocks propagate to the real economy with a lag. This mechanism underlies the empirical finding that revisions forecast both spreads and real outcomes over medium horizons.

Gilchrist and Zakrajšek (2012) Decomposition Finally, we examine how the information channel maps into the standard Gilchrist and Zakrajšek (2012) decomposition of credit spreads into a default component and a residual component, often interpreted as an excess bond premium.

The top panel of Table 10 reports the results from applying regression (1) to each component of spreads separately. Two key findings emerge. First, both revisions in expected profitability and their dispersion significantly predict not only the default component of spreads, but also the residual component. Second, the predictive effects are economically meaningful and persistent across horizons, mirroring the patterns documented in the data.

These results are striking in light of the model structure. By construction, there is no true excess bond premium in the model: investors are risk-neutral and prices reflect expected payoffs given available information. Nevertheless, the regression-based decom-

Table 10: Gilchrist and Zakrajšek (2012) Decomposition

	Forecasting Credit Spread$_{t+1}$	
	EBP$_{t+1}$	Expected Default$_{t+1}$
rev$_t$	-0.019*	-0.026**
[t]	[-1.78]	[-2.15]
σ_t^{rev}	0.011*	0.016**
[t]	[2.20]	[2.20]
N	149	149
	Forecasting Investment$_{t+1}$	
	spr$_t$ = EBP$_t$	spr$_t$ = Expected Default$_t$
spr$_t$	-0.017*	-0.022*
[t]	[-1.82]	[-1.93]
N	149	149

Note: The top panel summarizes the results of model-implied regressions of different components of corporate bond spreads (one-quarter ahead) on current investor expectations of corporate profits and its noise. We follow the procedure in Gilchrist and Zakrajšek (2012) to decompose bond spread into excess bond premium and the default component, and then run regression 1 on each component. The lower panel summarizes the results of forecasting aggregate investment (one-quarter ahead) using the current EBP and default component. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

position generates a sizable and time-varying residual component that behaves like an excess bond premium and responds systematically to information shocks.

The mechanism underlying this result follows directly from the model's informational friction. Because investors observe only noisy signals of fundamentals, they form beliefs about default risk that evolve gradually. At the same time, imperfect information induces state-dependent recovery rates, as firms enter default with balance sheets that have not fully adjusted to underlying conditions. This generates a nonlinear relationship between spreads and default probabilities, driven by the endogenous covariance between default likelihood and recovery rates. The linear projection underlying the Gilchrist and Zakrajšek (2012) decomposition does not capture this nonlinearity. As a result, part of the variation in expected losses – specifically, the component arising from time-varying recovery rates – is assigned to the residual. In this sense, the model provides a reinterpretation of the excess bond premium: it reflects an information-driven wedge in expected losses, rather than compensation for risk.

The lower panel of Table 10 shows that both components of spreads – default and residual – have predictive power for future real activity. In particular, increases in either component forecast declines in investment at medium horizons, consistent with the empirical evidence. Taken together, information shocks affect both perceived default probabilities and expected recovery rates, and through this channel influence financing conditions and real activity.

5 Conclusion

In order to better understand the consequences of information imperfections in debt markets on investment and business cycles, we have combined (1) macro and micro empirics linking professional forecasts of corporate profits to credit spreads and corporate investment with (2) a novel business cycle model of credit cycles with learning. Consistent with the idea that debt investors form beliefs about firms' creditworthiness using publicly-available information on short-term corporate profits, we have documented that changes in quarter-ahead professional forecasts of corporate profits have strong predictive power for credit spreads and investment over long horizons, both in the aggregate and at the firm level. Second, we have developed a quantitative macro model that incorporates this mechanism and have shown that its ability to account for key stylized facts of the credit-

cycles is superior to the rational learning benchmark. As such, we show that learning from noisy information is an important propagation mechanism for understanding credit and business cycles.

There are several venues along which our approach can be extended. First, motivated by the strong evidence of predictability in debt markets of Greenwood and Hanson (2013), we have focused on informational inefficiencies in debt markets. While predictability is relatively weaker in equity markets, it would be interesting to add agency issues in equity markets and explore whether they reinforce our mechanism. Second, an advantage of our quantitative model is that it can be readily extended for policy evaluation of alternative financial stability tools. Such an extension would allow for quantitative and welfare evaluation of policy counterfactuals of the effectiveness of monetary policy or other policy measures aimed at stabilizing financial markets in times of stress. Finally, our framework could be extended to study in more detail additional forces that may lead to fragility in credit markets, including, for example, relative-performance evaluation type features in institutional investors' compensation contracts (Feroli, Kashyap, Schoenholtz, and Shin, 2014).

While we look forward to these extensions, we believe that the approach developed in this paper offers a useful first take on informational inefficiencies in financial markets, which had not yet been the subject of formal analysis and testing despite the fact that learning is a central idea in modern business cycle theory.

References

Acharya, Viral V., Sreedhar T. Bharath, and Anand Srinivasan (2007). Does Industry-Wide Distress Affect Defaulted firms? Evidence from Creditor Recoveries. *Journal of Financial Economics 85*(3), 787–821.

Alfaro, Ivan, Nicholas Bloom, and Xiaoji Lin (2024). The Finance Uncertainty Multiplier. *Journal of Political Economy 132*(2), 577–615.

Arellano, Cristina, Yan Bai, and Patrick J. Kehoe (2019). Financial Frictions and Fluctuations in Volatility. *Journal of Political Economy 127*(5), 2049–2103.

Bernanke, Ben, Mark Gertler, and Simon Gilchrist (1999). The financial accelerator in a

quantitative business cycle framework. In Ben Friedman and Michael Woodford (Eds.), *Handbook of Macroeconomics*, Chapter 21. Elsevier.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer (2018). Diagnostic Expectations and Credit Cycles. *Journal of Finance 73*(1), 199–227.

Bordalo, Pedro, Nicola Gennaioli, Andrei Shleifer, and Stephen Terry (2019). Real Credit Cycles. Working Paper, Harvard University.

Bouchaud, Jean-Philippe, Philipp Kruger, Augustin Landier, and David Thesmar (2019). Sticky Expectations and the Profitability Anomaly. *Journal of Finance 74*(2), 639–674.

Buera, Francisco J, Joseph P Kaboski, and Yongseok Shin (2011). Finance and development: A tale of two sectors. *American economic review 101*(5), 1964–2002.

Carlstrom, Charles T. and Timothy S. Fuerst (1997). Agency Costs, Net Worth, and Business Fluctuations: A Computable General Equilibrium Analysis. *American Economic Review 87*(5), 893–910.

Coibion, Olivier, Yuriy Gorodnichenko, and Tiziano Ropele (2020). Inflation Expectations and Firm Decisions: New Causal Evidence. *Quarterly Journal of Economics 135*, 165–219.

Coibion, O., Y. Gorodnichenko, and Kumar Saten (2018). How Do Firms Form Their Expectations? New Survey Evidence. *American Economic Review 108*, 2671–2713.

Collard, Fabrice, Harris Dellas, and Frank Smets (2009). Imperfect information and the business cycle. *Journal of Monetary Economics 56*, S38–S56.

Collin-Dufresn, Pierre, Robert S Goldstein, and J Spencer Martin (2001). The Determinants of Credit Spread Changes. *Journal of Finance 56*(6), 2177–2207.

Driessen, Joost (2005). Is Default Event Risk Priced in Corporate Bonds? *The Review of Financial Studies 18*(1), 165–195.

Fazzari, Steven, R Glenn Hubbard, and Bruce C Petersen (1988). Financing Constraints and Corporate Investment. Brookings Papers on Economic Activity.

Feroli, Michael, Anil K. Kashyap, Kermit Schoenholtz, and Hyun Song Shin (2014). Market Tantrums and Monetary Policy. Proceedings of U.S. Monetary Policy Forum.

Fracassi, Cesare, Stefan Petry, and Geoffrey Tate (2016). Does rating analyst subjectivity affect corporate debt pricing? *Journal of Financial Economics 120*(3), 514–538.

Gertler, Mark and Peter Karadi (2011). A model of unconventional monetary policy. *Journal of Monetary Economics 58*, 17–34.

Gertler, Mark and Nobuhiro Kiyotaki (2010). Financial Intermediation and Credit Policy in Business Cycle Analysis. *Handbook of Monetary Economics 3*, 547–599.

Gilchrist, Simon, Jae W. Sim, and Egon Zakrajšek (2014). Uncertainty, Financial Frictions, and Investment Dynamics. NBER Working Paper No. 20038.

Gilchrist, Simon and Egon Zakrajšek (2012). Credit Spreads and Business Cycle Fluctuations. *American Economic Review 102*(4), 1692–1720.

Gomes, João F. and Lukas Schmid (2020). Equilibrium Asset Pricing with Leverage and Default. *Journal of Finance* (forthcoming).

Graham, John R. (2000). How Big Are the Tax Benefits of Debt? *Journal of Finance 55*(5), 1901–1941.

Greenwood, Robin and Samuel G. Hanson (2013). Issuer Quality and Corporate Bond Returns. *Review of Financial Studies 26*(6), 1483–1525.

Greenwood, Robin, Samuel G. Hanson, and Lawrence J. Jin (2019). Reflexivity in Credit Markets. NBER Working Paper No. 25747.

Guvenen, Fatih (2007). Learning Your Earning: Are Labor Income Shocks Really Very Persistent? *American Economic Review 97*(3), 687–712.

Hamilton, David T., Sharon Ou, Frank Kim, and Richard Cantor (2007, February). Corporate Default and Recovery Rates, 1920–2006. Special Comment 102071, Moody's Investors Service, New York.

He, Zhiguo and Arvind Krishnamurthy (2013). Intermediary Asset Pricing. *American Economic Review 103*(2), 732–70.

Hennessy, Christopher A. and Toni M. Whited (2007). How Costly is External Financing? Evidence from a Structural Estimation. *Journal of Finance 62*(4), 1705–1745.

Hong, Harrison and Marcin Kacperczyk (2010). Competition and Bias. *Quarterly Journal of Economics 125*, 1683–1725.

Khan, Aubhik, Tatsuro Senga, and Julia K Thomas (2014). Default Risk and Aggregate Fluctuations in an Economy with Production Heterogeneity. Working Paper.

Krishnamurthy, Arvind and Wenhao Li (2025). Dissecting Mechanisms of Financial Crises: Intermediation and Sentiment. *Journal of Political Economy 133*(3).

López-Salido, David, Jeremy C. Stein, and Egon Zakrajšek (2017). Credit-market sentiment and the business cycle. *Quarterly Journal of Economics 132*(3), 1373–1426.

Lorenzoni, Guido (2009). A Theory of Demand Shocks. *American Economic Review 99*(5), 2050–84.

Lucas, Robert E. (1972). Expectations and the Neutrality of Money. *Journal of Economic Theory 4*(2), 103–24.

Maćkowiak, Bartosz and Mirko Wiederholt (2009). Optimal Sticky Prices under Rational Inattention. *American Economic Review 99*(3), 769–803.

Newey, Whitney K. and Kenneth D. West (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica 55*(3), 703–708.

Sims, Christopher (2003). Implications of Rational Inattention. *Journal of Monetary Economics 50*(3), 665–690.

Townsend, Robert M (1979). Optimal contracts and competitive markets with costly state verification. *Journal of Economic theory 21*(2), 265–293.

Woodford, Michael (2003). Imperfect common knowledge and the effects of monetary policy. In Frydman R. Stiglitz J. Woodford M. Aghion, P. (Ed.), *Knowledge, Information, and Expectations in Modern Macroeconomics: In Honor of Edmund S. Phelps*, pp. 25–58. Princeton University Press.

Information Spreads (Online Appendix)

Antonio Falato Joseph Kaboski Jasmine Xiao

March 2026

A A Model with Forecaster-Specific Signals

Suppose there are N forecasters, and each of them receives a private signal s_t^i ($i = 1, 2, ..., N$) about the aggregate shock ε_t^z, where:

$$s_t^i = \varepsilon_t^z + u_t^i$$

and the idiosyncratic noise is i.i.d. normal, $u_t^i \sim N(u_t, \widetilde{\sigma}_{ut}^2)$. Note that we use $\widetilde{\sigma}_{ut}^2$ to denote the variance of u_{it}, to differentiate from the variance of u_t, σ_{ut}^2, in equation (15).

The mean signal across the forecasters at time t is therefore:

$$\begin{aligned} \mathrm{E}[s_t^i] &= \frac{1}{N}\sum_{i=1}^{N}\left[\varepsilon_t^z + u_t^i\right] \\ &= \varepsilon_t^z + \frac{1}{N}\sum_{i=1}^{N} u_t^i \\ &= \varepsilon_t^z + u_t, \end{aligned} \tag{A.1}$$

where the right-hand size coincides with that of equation (15); in other words, the average signal across forecasters here is the public signal in the dynamic model. Furthermore, the variance of the aggregate noise σ_{ut}^2 can also be written as:

$$\begin{aligned} \mathrm{Var}(u_t) &= \mathrm{Var}\Big(\frac{1}{N}\sum_{i=1}^{N} u_t^i\Big) \\ &= \frac{1}{N^2} N \widetilde{\sigma}_{ut}^2 = \frac{1}{N}\widetilde{\sigma}_{ut}^2. \end{aligned}$$

Thus, an increase in the dispersion of signals (due to widening $\widetilde{\sigma}_{ut}$) received by individual forecasters directly leads to an increase in the aggregate uncertainty (σ_{ut}).

B State-Space Representation

In the model, agents observe their own productivity a_{jt} and an aggregate signal s_t, but they do not observe the latent aggregate state z_t. We can rewrite equations (11), (12) and (15) in state-space form. The state equation is the following:

$$\alpha_t = A\alpha_{t-1} + Bv_t \tag{A.2}$$

where

$$\alpha_t = \begin{bmatrix} z_t \\ z_{t-1} \end{bmatrix}, \; A = \begin{bmatrix} \rho_z & 0 \\ 1 & 0 \end{bmatrix}, \; v_t = \begin{bmatrix} \varepsilon_t^z \\ \varepsilon_{t-1}^z \end{bmatrix}, \; B = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix},$$

and $\varepsilon_t^z \sim iidN(0, \sigma_\varepsilon)$. The measurement equation is:

$$x_{jt} = C\alpha_t + \zeta_t \tag{A.3}$$

where

$$x_{jt} = \begin{bmatrix} s_t \\ a_{jt} \end{bmatrix}, \; C = \begin{bmatrix} 1 & -\rho_z \\ 1 & 0 \end{bmatrix}, \; \zeta_t = \begin{bmatrix} u_t \\ \eta_{jt} \end{bmatrix} \sim iidN\left(\begin{bmatrix} 0 \\ \mu_\eta \end{bmatrix}, \begin{bmatrix} \sigma_{ut} & 0 \\ 0 & \sigma_\eta \end{bmatrix} \right).$$

ε_t^z, u_t and η_{jt} are mutually uncorrelated.

At each t, we estimate the posterior density of z_t given the history $\Omega_{jt} = \{a_{jt}, s_t, \sigma_{ut}, a_{jt-1}, s_{t-1}, \sigma_{ut-1}, ..., a_{j0}, s_0, \sigma_{u0}\}$ using the Kalman filter. Let $z_{jt|t}$ and $\Theta_{jt|t}$ denote the estimated conditional mean and variance. Thus, we find $z_{jt|t}$ and $\Theta_{jt|t}$ for each quarter in 1985Q1-2010Q4 using an expanding window of the revision series (s_t) and its dispersion (σ_{ut}) from 1970Q1 to the current quarter. We then use the values to jointly solve the discretized firm's problem and the debt market equilibrium.

C Discretized Model

A Baseline Model

In what follows, we omit the subscript j for notational simplicity. Let $\widehat{z} \equiv z_{t|t}$ and $\Theta \equiv \Theta_{t+1|t}$. We solve the following problem:

$$V(b,x,\widehat{z},\Theta) = \max_{b',k',e} \Bigg\{ e(b,x,k',b',\widehat{z},\Theta) \; + \beta \sum_{\eta'} \sum_{z'} \sum_{\widehat{z}'} \sum_{\Theta'} \Big(1 - 1_{\text{default}}(b',k',z',\eta',\widehat{z}',\Theta')\Big) \\ \times V\Big(b', x(z',\eta',b',k'), \widehat{z}', \Theta'\Big) \Pi_\eta(\eta') \Pi_z(z'|\widehat{z},\Theta) \Pi_{\widehat{z}(\widehat{z}'|\widehat{z},\Theta)} \Pi_\Theta(\Theta') \Bigg\},$$

subject to:

$$\begin{aligned} & e = x - k' + q(b',k',\widehat{z},\Theta)\Big(b' - (1-\lambda)b\Big) \geq 0 \\ & b' - (1-\lambda)b \geq 0 \\ & 1_{\text{default}}(b',k',z',\eta',\widehat{z}',\widehat{\Theta}') = 1 \;\text{ if }\; e\Big(b', x(z',\eta',b',k'), k'', b'', \widehat{z}', \widehat{\Theta}'\Big) < 0 \\ & k'' = g_k\Big(b', x(z',\eta',b',k'), \widehat{z}', \widehat{\Theta}'\Big) \text{ and } b'' = g_b\Big(b', x(z',\eta',b',k'), \widehat{z}', \widehat{\Theta}'\Big). \end{aligned}$$

Bond pricing function becomes:

$$q(b',k',\widehat{z},\Theta) = \beta \times \Bigg[\sum_{\eta'} \sum_{z'} \sum_{\widehat{z}'} \sum_{\Theta'} \Big(1 - 1_{\text{default}}(b',k',z',\eta',\widehat{z}',\Theta')\Big) \\ \underbrace{\Big[c + \lambda + (1-\lambda) q\big(b'',k'',\widehat{z},\Theta\big)\Big]}_{\text{no default payoff}} \times \Pi_\eta(\eta') \Pi_z(z'|\widehat{z},\Theta) \Pi_{\widehat{z}(\widehat{z}'|\widehat{z},\Theta)} \Pi_\Theta(\Theta') \\ + \sum_{\eta'} \sum_{z'} \sum_{\widehat{z}'} \sum_{\Theta'} 1_{\text{default}}(b',k',z',\eta',\widehat{z}',\Theta') \underbrace{B(b',k',\eta',z',\widehat{z}',\Theta')}_{\text{recovery rate in default}} \times \Pi_\eta(\eta') \Pi_z(z'|\widehat{z},\Theta) \widehat{\Pi}_z(\widehat{z}'|\widehat{z},\Theta) \Pi_\Theta(\Theta') \Bigg]$$

where:

$$B(b',k',\eta',z',\widehat{z}',\Theta') = V\Big(0, x(z',\eta',0,(1-\xi)(1-\delta)k'), \widehat{z}', \Theta'\Big) \frac{1}{b'}.$$

B Model with Constant σ_u

When the noise term u_t in (15) has a constant variance, the conditional variance of a Kalman filter converges quickly to the steady state. As a result, we can remove Θ from the firm's state, and the problem becomes:

$$V(b,x,\widehat{z}) = \max_{b',k',e} \Bigg\{ e(b,x,k',b',\widehat{z}) + \beta \sum_{\eta'} \sum_{z'} \sum_{\widehat{z}'} \Big(1 - 1_{\text{default}}(b',k',z',\eta',\widehat{z}')\Big) V\Big(b', x(z',\eta',b',k'), \widehat{z}'\Big) \Pi_\eta(\eta') \Pi_z(z'|\widehat{z}) \Pi_{\widehat{z}(\widehat{z}'|\widehat{z})} \Bigg\}.$$

Bond pricing function becomes:

$$q(b',k',\widehat{z}) = \beta \times \Bigg[\sum_{\eta'} \sum_{z'} \sum_{\widehat{z}'} \Big(1 - 1_{\text{default}}(b',k',z',\eta',\widehat{z}')\Big) \underbrace{\Big[c + \lambda + (1-\lambda) q\big(b'',k'',\widehat{z}'\big)\Big]}_{\text{no default payoff}} \Pi_\eta(\eta') \Pi_z(z'|\widehat{z}) \Pi_{\widehat{z}(\widehat{z}'|\widehat{z})}$$
$$+ \sum_{\eta'} \sum_{z'} \sum_{\widehat{z}'} 1_{\text{default}}(b',k',z',\eta',\widehat{z}') \underbrace{B(b',k',\eta',z',\widehat{z}')}_{\text{recovery rate in default}} \Pi_\eta(\eta') \Pi_z(z'|\widehat{z}) \widehat{\Pi}_z(\widehat{z}'|\widehat{z}) \Bigg]$$

where:

$$B(b',k',\eta',z',\widehat{z}',\Theta') = V\Big(0, x(z',\eta',0,(1-\xi)(1-\delta)k'), \widehat{z}'\Big) \frac{1}{b'}.$$

C Full Information Model

The full information rational expectations model is a standard firm investment model with defaultable long-term debt. The key difference from the imperfect information model is that the true TFP (z) is a state in both the firm problem and the bond pricing equilibrium. In addition, when we compute expectations, we use the true conditional density $f(z'|z)$, instead of the density conditional on available information $f(z'|\Omega)$. The discretized firm problem is thus:

$$V(b,x,z) = \max_{b',k',e} \Bigg\{ e(b,x,k',b',z) + \beta \sum_{\eta'} \sum_{z'} \Big(1 - 1_{\text{default}}(b',k',z',\eta',z')\Big) V\Big(b', x(z',\eta',b',k'), z'\Big) \Pi_\eta(\eta') \Pi_z(z'|z) \Bigg\}.$$

Bond pricing function becomes:

$$q(b',k',z) = \beta \times \Bigg[\sum_{\eta'} \sum_{z'} \sum_{\widehat{z}'} \Big(1 - 1_{\text{default}}(b',k',z',\eta',\widehat{z}')\Big) \underbrace{\Big[c + \lambda + (1-\lambda) q\big(b'',k'',z'\big)\Big]}_{\text{no default payoff}} \Pi_\eta(\eta') \Pi_z(z'|z) + \sum_{\eta'} \sum_{z'} \sum_{\widehat{z}'} 1_{\text{default}}(b',k',z',\eta',\widehat{z}') \underbrace{B(b',k',\eta',z',\widehat{z}')}_{\text{recovery rate in default}} \Pi_\eta(\eta') \Pi_z(z'|z) \Bigg]$$

where:

$$B(b',k',\eta',z',\widehat{z}',\Theta') = V\Big(0, x(z',\eta',0,(1-\xi)(1-\delta)k'), z'\Big) \frac{1}{b'}.$$

Table A.1: Summary Statistics of Aggregate Data

Panel A: Expectations of Corporate Profits, Aggregate Level					
Year	rev_t	σ_t^{rev}	Year	rev_t	σ_t^{rev}
1971	-0.05	0.09	1991	-0.01	0.76
1972	-0.00	0.07	1992	0.33	0.63
1973	0.09	0.10	1993	0.04	0.44
1974	0.25	0.20	1994	0.24	0.61
1975	-0.02	0.48	1995	0.10	0.52
1976	-0.07	0.17	1996	0.24	0.71
1977	0.06	0.16	1997	0.39	0.65
1978	0.04	0.34	1998	-0.18	0.95
1979	0.17	0.29	1999	0.76	0.59
1980	0.09	0.44	2000	0.42	0.82
1981	0.18	0.71	2001	-1.27	1.08
1982	-0.16	0.45	2002	-0.49	1.34
1983	-0.06	0.48	2003	-0.10	1.11
1984	-0.16	0.28	2004	1.05	1.63
1985	-011	0.34	2005	1.57	1.69
1986	-0.08	0.28	2006	-0.09	2.07
1987	-0.09	0.31	2007	-0.38	3.40
1988	0.20	0.36	2008	-0.86	3.60
1989	-0.16	0.28	2009	-0.46	3.86
1990	0.08	0.28	2010	1.29	2.13
			Mean	0.06	0.86
			St Dev	1.00	1.00
			N	151	151

Panel B: Credit Spreads and Business Cycle Variables, Aggregate Level				
	Mean	St.Dev	Min	Max
GZ Spread	1.59	1.03	0.56	7.66
GDP Growth	0.70	0.85	-2.05	3.93
Investment Growth	1.08	2.49	-10.28	8.43

Note: This table presents the summary for our aggregate variables over the sample period. We measure investor expectations of corporate profits, rev_t, as the current revision in investors' expectations of next quarter corporate profits. The measure is constructed as the change between current and last period's investor expectations of next quarter corporate profits. We measure noise in investor expectations of corporate profits, σ_t^{rev}, as the dispersion (standard deviation) of revisions across individual forecasters. To ease economic interpretation, the measures are re-scaled by their respective unconditional standard deviation. Quarterly information on expectations at the aggregate level is from the Survey of Professional Forecasters.

Table A.2: Summary Statistics of Micro Data

Panel A: Expectations of Corporate Profits, Firm Level				
	Mean	St.Dev	Min	Max
rev_{it}	-0.79	1.00	-5.55	1.67
$\varepsilon_{it}^{\text{rev}}$	0.02	1.00	-3.28	3.21
σ_{it}^{rev}	0.97	1.00	0.02	6.09
$\sigma_{it}^{\varepsilon^{\text{rev}}}$	1.10	1.00	0.04	5.98
Observations		245,908		
Firms		10,396		
Panel B: Spreads and Other Variables, Firm Level				
	Mean	St.Dev	Min	Max
Spread_{it}	1.70	2.25	-2.20	13.19
Observations		189,507		
Bonds		4,963		
Firms		775		
Capex growth_{it}	-0.13	1.92	-6.76	5.36
Total assets_{it} ($ billion)	10.42	13.95	0.29	58.28
ROA_{it}	3.58	1.94	-0.98	9.14
Observations		21,874		
Firms		769		

Note: This table presents the summary for our firm-level variables over our sample period 1982-2010. We measure investor expectations of corporate profits, rev_{it}, as the current revision in investors' expectations of next quarter corporate profits. The measure is constructed as the change between current and last period's investor expectations of next quarter corporate profits. We also consider a residualized version of rev_{it}, Shock to rev_{it} ($\varepsilon_{it}^{\text{rev}}$), which is constructed as the analyst-specific component which is orthogonal to the firm-specific component of rev_{it}. To ease economic interpretation, the measures are re-scaled by their respective unconditional standard deviation. Quarterly information on expectations at the firm level is from IBES. Bond-level spreads are monthly from ICE/IDC for 1998-2010 and from the Warga database for 1982-1997. Quarterly firm balance sheet information is from Compustat.

Table A.3: Time-Series Correlations Between Credit Spreads and Expectations

	Panel A: Baseline (1973-2010)				
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
rev_t	-0.195**	-0.209**	-0.107	-0.069	-0.022
[t]	[-2.21]	[-2.03]	[-1.19]	[-0.70]	[-0.44]
σ_t^{rev}	0.625***	0.634***	0.678***	0.655***	0.726***
[t]	[6.04]	[5.42]	[4.44]	[5.30]	[5.23]
N	151	151	151	151	150
R^2	0.35	0.38	0.40	0.35	0.36
	Panel B: Longer Sample (1973-2024)				
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
rev_t	-0.165**	-0.173**	-0.121	-0.081	0.014
[t]	[-2.11]	[-1.83]	[-1.40]	[-1.02]	[0.25]
σ_t^{rev}	0.207***	0.209***	0.217***	0.181**	0.170**
[t]	[3.26]	[2.99]	[2.60]	[2.46]	[2.37]
N	208	207	206	205	201
R^2	0.07	0.08	0.07	0.04	0.03

Note: This table summarizes the results of time-series forecasting regressions of corporate bond spreads on investor expectations of corporate profits and its noise without controls (regression 1 without ΓX_{t-1}). t-statistics for k-period forecasting regressions are based on Newey-West (1987) standard errors, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Table A.4: Additional Aggregate Evidence on Forecasting Investment and Output

	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
Output growth					
$\widehat{\text{spr}}_{t+1}$	-0.372	-0.753*	-0.795**	-0.820**	-0.240
[t]	[-1.22]	[-1.96]	[-2.10]	[-2.34]	[-0.72]
N	148	147	146	145	141
R^2	0.317	0.213	0.508	0.175	0.093
Investment growth					
$\widehat{\text{spr}}_{t+1}$	-0.287	-0.730***	-0.887***	-1.40***	-0.940
[t]	[-1.04]	[-2.68]	[-3.07]	[-3.92]	[-1.64]
N	148	147	146	145	141
R^2	0.538	0.458	0.366	0.299	0.214

Note: This table summarizes the results of time-series forecasting regressions of the quarter-on-quarter output growth and business investment growth, in turn, on the component of credit spreads that is predictable (from regression 1) based on our measures of investor expectations (see regression 2). t-statistics for k-period forecasting regressions are based on Newey-West (1987) standard errors, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Table A.5: Additional Micro Evidence on Forecasting Firm Investment

$\text{IV}_{it} = \varepsilon_{it}^{\text{rev}}, \sigma_{it}^{\varepsilon^{\text{rev}}}$					
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
$\widehat{\text{spr}}_{t+1}$	0.289	-0.472	-0.846*	-0.950**	-0.676*
[t]	[0.62]	[-1.06]	[-1.76]	[-2.12]	[-1.82]
Time FE	Yes	Yes	Yes	Yes	Yes
N	13,660	13,386	13,081	12,725	11,387
Firms	635	629	620	610	585

Note: This table summarizes the results of firm-level forecasting regressions of investment on the predicted-component of credit spread from the IV regression using "shocks" to revisions and its dispersion (Panel A of Table 4). t-statistics are based on standard errors that are clustered at the bond level to allow for within-bond serial correlation, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Table A.6: Micro Evidence on Forecasting Firm Debt Issuance

Panel A: $\widehat{\text{spr}}_{t+1}$ predicted from rev_{it} and $\sigma_{it}^{\varepsilon^{\text{rev}}}$					
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
$\widehat{\text{spr}}_{t+1}$	-0.211	-0.503	-1.413***	-1.017*	0.112
[t]	[-0.45]	[-0.98]	[-2.71]	[-1.92]	[0.24]
Time FE	Yes	Yes	Yes	Yes	Yes
N	12,390	12,125	11,837	11,549	10,450
Firms	619	614	605	594	577
Panel B: $\widehat{\text{spr}}_{t+1}$ predicted from "shocks" $\varepsilon_{it}^{\text{rev}}$ and $\sigma_{it}^{\varepsilon^{\text{rev}}}$					
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
$\widehat{\text{spr}}_{t+1}$	0.276	-1.861***	-0.648	-0.022	-0.152
[t]	[0.42]	[-2.52]	[-1.04]	[-0.03]	[-0.28]
Time FE	Yes	Yes	Yes	Yes	Yes
N	12,304	12,037	11,750	11,463	10,362
Firms	615	610	600	590	572

Note: This table summarizes the results of firm-level forecasting regressions of debt issuance on the predicted-component of credit spread from: (i) regression 3 (Panel A); (ii) regressions 7-9 (Panel B). t-statistics are based on standard errors that are clustered at the bond level to allow for within-bond serial correlation, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Table A.7: Additional Results on the Impact of "Shocks" to Revisions on Credit Spreads Using IV

$\text{IV}_{it} = \varepsilon_{it}^{\text{rev}}, \sigma_{it}^{\varepsilon^{\text{rev}}}$					
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
$\widehat{\text{rev}}_{it}$	-0.009	-0.150*	-0.323***	-0.117	0.161
[t]	[-0.13]	[-1.71]	[-3.07]	[-0.95]	[1.01]
$\widehat{\sigma}_{it}^{\text{rev}}$	0.263***	0.196***	0.169**	0.338***	0.661***
[t]	[5.07]	[3.21]	[2.23]	[3.77]	[5.38]
Time FE	Yes	Yes	Yes	Yes	Yes
N	72,680	67,671	61,215	55,580	38,014
Bonds	4,031	3,794	3,611	3,437	2,827

Note: This table summarizes additional firm-level evidence using two-stage least squares with instrumental variables. The instruments are residualized rev_{it}, $\varepsilon_{it}^{\text{rev}}$, and its noise, $\sigma_{it}^{\varepsilon^{\text{rev}}}$. The key difference from the results in Table 4 is that here the firm-level shocks $\varepsilon_{it}^{\text{rev}}$ are estimated with analyst fixed effects, instead of the analyst-time fixed effects shown in (5). We exclude firms that have only 2 analysts covering them in a given quarter. t-statistics are based on standard errors that are clustered at the bond level to allow for within-bond serial correlation, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Table A.8: Placebo Tests on Instruments

Dependent Var: Instrument for revisions ($\varepsilon_{it}^{\text{rev}}$)					
	$k=1$	$k=2$	$k=3$	$k=4$	$k=8$
profit_{it-k}	0.011	-0.011	0.029	0.025	0.027
[t]	[0.37]	[-0.39]	[1.23]	[1.06]	[0.84]
N	13,739	13,540	13,424	13,246	12,776
R^2	0.0000	0.0000	0.0001	0.0001	0.0001

Note: In this table, we regress our analyst instrument for revisions ($\varepsilon_{it}^{\text{rev}}$), estimated from equation (6), on different lags ($k = 1,2,3,4,8$) of past firm profits. In our setting, the main threat to identification is selection – e.g. if optimistic analysts sort into more profitable firms. If this were the case, we would expect a positive correlation between past profits and our analyst-based instrument. As shown in this table, we do not find any significant correlations.

Table A.9: Impact of "Shocks" to Revisions on Different Components of Spreads

Panel A: spr_{it+k} = excess bond premium (EBP), $IV_{it} = \varepsilon_{it}^{rev}, \sigma_{it}^{\varepsilon^{rev}}$					
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
$\widehat{rev}_{it}$	-0.063	-0.101**	0.021	0.044	0.020
[t]	[-1.50]	[-2.03]	[0.39]	[0.67]	[0.26]
$\widehat{\sigma}_{it}^{rev}$	0.017	0.017	0.047**	0.070***	0.199***
[t]	[0.84]	[0.72]	[1.73]	[2.20]	[4.84]
Time FE	Yes	Yes	Yes	Yes	Yes
N	96,927	91,389	82,780	74,960	52,342
Bonds	3,404	3,243	3,115	2,961	2,487
Panel B: spr_{it+k} = default component, $IV_{it} = \varepsilon_{it}^{rev}, \sigma_{it}^{\varepsilon^{rev}}$					
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
$\widehat{rev}_{it}$	-0.025**	-0.030**	-0.058***	-0.013	-0.012
[t]	[-2.56]	[-2.13]	[-3.52]	[-0.68]	[-0.46]
$\widehat{\sigma}_{it}^{rev}$	0.025***	0.041***	0.046***	0.070***	0.074***
[t]	[6.00]	[6.79]	[6.29]	[7.98]	[5.77]
Time FE	Yes	Yes	Yes	Yes	Yes
N	96,927	91,389	82,780	74,960	52,342
Bonds	3,404	3,243	3,115	2,961	2,487

Note: This table summarizes the results of firm-level forecasting regressions of different components of corporate bond spreads on investor expectations of corporate profits and its noise. We follow the procedure in Gilchrist and Zakrajšek (2012) to decompose the corporate bond spread into the excess bond premium (Panel A) and the default component (Panel B). We then use two-stage least squares with instrumental variables – the residualized rev_{it}, ε_{it}^{rev}, and its noise, $\sigma_{it}^{\varepsilon^{rev}}$. t-statistics are based on standard errors that are clustered at the bond level to allow for within-bond serial correlation, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Table A.10: Credit Spreads and Forecast Errors

	Panel A: Aggregate Data				
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
FE_t	-0.117*	-0.210**	-0.193**	-0.187**	-0.132*
[t]	[-1.90]	[-2.14]	[-2.24]	[-2.03]	[-1.86]
σ_t^{FE}	0.140*	0.236***	0.491**	0.512***	0.578***
[t]	[1.72]	[2.69]	[2.48]	[3.43]	[2.45]
Macro Controls	Yes	Yes	Yes	Yes	Yes
N	148	147	146	145	141
	Panel B: Micro Data				
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
FE_{it}	-0.077***	-0.083***	-0.104***	-0.103***	-0.091***
[t]	[-10.32]	[-8.86]	[-8.64]	[-7.19]	[-3.36]
σ_{it}^{FE}	0.072***	0.082***	0.099***	0.111***	0.124***
[t]	[9.58]	[9.14]	[9.00]	[7.71]	[5.78]
Time FE	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes
N	116,951	109,649	99,466	90,226	62,712
Bonds	4,089	3,866	3,682	3,497	2,910

Note: This table summarizes the results of time-series forecasting regressions of corporate bond spreads on forecast errors of corporate profits and its dispersion. Forecast errors are defined as forecasts minus realized corporate profits. Panel A presents the regression results using aggregate data (analogous to regression 1)); Panel B presents the results using micro data (analogous to regression 3). t-statistics are based on Newey-West (1987) standard errors (Panel A), or standard errors that are clustered at the bond level to allow for within-bond serial correlation (Panel B), with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Table A.11: Additional Micro Evidence Controlling for Uncertainty Shocks

Panel A: proxy based on realized stock return volatility					
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
rev_{it}	-0.049***	-0.043***	-0.029***	-0.031***	0.030
[t]	[-6.46]	[-4.84]	[-2.93]	[-2.68]	[1.43]
σ_{it}^{rev}	0.043***	0.056***	0.066***	0.080***	0.147***
[t]	[4.92]	[4.87]	[4.70]	[4.55]	[4.90]
Time FE	Yes	Yes	Yes	Yes	Yes
N	93,733	87,088	80,070	72,370	48,791
Bonds	3,518	3,276	3,114	2,908	2,275
Panel B: proxy based on option implied voatility					
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
$\widehat{\text{rev}}_{it}$	-0.058***	-0.052***	-0.035***	-0.032**	0.036
[t]	[-6.05]	[-4.51]	[-2.61]	[-2.02]	[1.31]
σ_{it}^{rev}	0.056***	0.074***	0.088***	0.115***	0.202***
[t]	[4.76]	[4.66]	[4.80]	[4.94]	[5.71]
Time FE	Yes	Yes	Yes	Yes	Yes
N	74,556	68,759	63,390	58,060	40,598
Firms	2,319	2,189	2,078	1,948	1,511
Panel C: instruments for firm exposures to various sources of uncertainty					
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
$\widehat{\text{rev}}_{it}$	-0.051***	-0.046***	-0.032***	-0.033***	0.033
[t]	[-6.79]	[-5.22]	[-3.18]	[-2.83]	[1.60]
σ_{it}^{rev}	0.038***	0.048***	0.054***	0.064***	0.132***
[t]	[4.32]	[4.12]	[4.84]	[3.59]	[4.49]
Time FE	Yes	Yes	Yes	Yes	Yes
N	93,733	87,088	80,070	72,370	48,791
Firms	3,518	3,276	3,114	2,908	2,275

Note: This table summarizes the additional results of firm-level forecasting regressions of corporate bond spreads on investor expectations of corporate profits and its noise (Panel A, see regression 3), controlling for uncertainty shock proxies from Alfaro, Bloom, and Lin (2024). Panel A adds an uncertainty shock proxy based on firm realized stock return volatility. Panel B adds an uncertainty shock proxy based on firm option implied volatility. Panel C adds the 9 instruments for uncertainty shocks based on the second moment exposures to 7 bilateral exchange rates with the US Dollar considered as "Major Currencies" by the US Fed Board (Euro, Canadian Dollar, Japanese Yen, British Pound, Swiss Franc, Australian Dollar, and Swedish Krona), crude-oil prices, and Economic Policy Uncertainty. All panels also add controls for firm-moment effects based on stock returns and Tobin's Q.

Table A.12: Parameterization (Full Information)

Parameter	Description	Model
Preferences and technology		
α	Returns to scale	0.65
δ	Depreciation rate	0.025
β	Time preference	0.99
$\overline{a}$	Mean productivity	-0.159
σ_η	Idiosyncratic shock (volatility)	0.0105
ρ_z	Aggregate shock persistence	0.93
σ_ε	Aggregate shock volatility	0.0073
f	Fixed cost	0.416
External financing		
τ	Corporate tax rate	0.3
ξ	Bankrupty cost	0.32
c	Coupon rate	0.0101
λ	Debt amortization rate	0.05

Table A.13: Parameterization (Constant σ_u)

Parameter	Description	Model
Preferences and technology		
α	Returns to scale	0.65
δ	Depreciation rate	0.025
β	Time preference	0.99
$\overline{a}$	Mean productivity	-0.156
σ_η	Idiosyncratic shock (volatility)	0.0105
ρ_z	Aggregate shock persistence	0.93
σ_ε	Aggregate shock volatility	0.0073
f	Fixed cost	0.3027
External financing		
τ	Corporate tax rate	0.3
ξ	Bankrupty cost	0.34
c	Coupon rate	0.0101
λ	Debt amortization rate	0.05
Information frictions		
μ_{σ_u}	Mean noise	0.006243
$\widehat{\rho}_z$	Persistence of conditional mean	0.936
$\sigma_{\widehat{\epsilon}}$	Std error of conditional mean	0.0068

Table A.14: Model-Implied Regressions (Full Information)

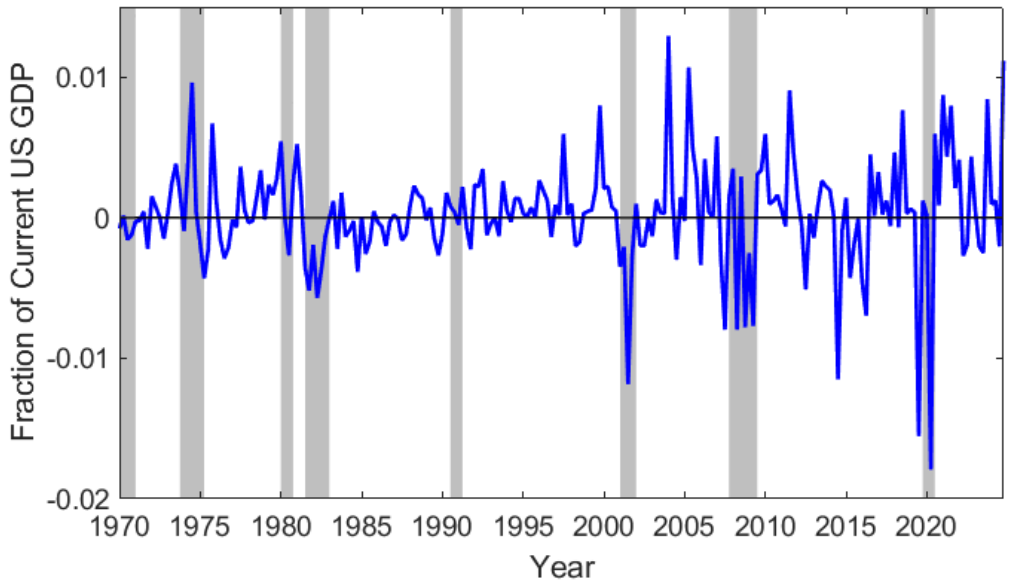
	Forecasting Credit Spreads			
	Data		Model	
	1-qtr	2-qtr	1-qtr	2-qtr
rev_t	-0.103*	-0.186**	0.003	-0.007
[t]	[-1.68]	[-2.07]	[0.21]	[-0.19]
σ_t^{rev}	0.181*	0.307**	0.006	0.011
[t]	[1.68]	[2.24]	[0.23]	[0.32]
N	148	147	150	149
	Forecasting Investment			
	Data		Model	
	1-qtr	2-qtr	1-qtr	2-qtr
$\widehat{\text{spr}}_{t+1}$	-0.287	-0.512*	0.012	0.014
[t]	[-1.04]	[-2.29]	[0.40]	[0.26]
N	148	147	150	149

Table A.15: Model-Implied Regressions (Constant σ_u)

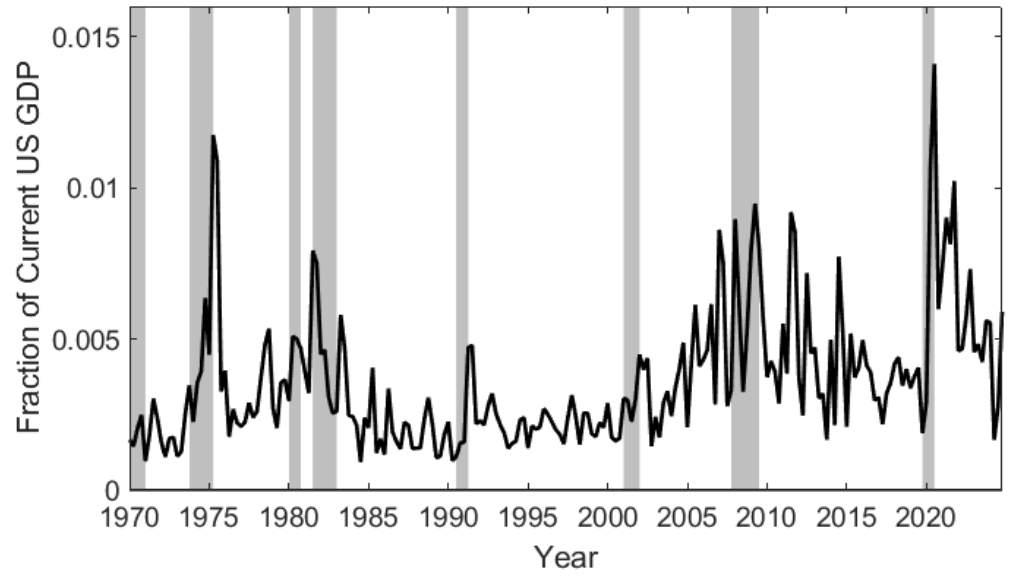
	Forecasting Credit Spreads			
	Data		Model	
	1-qtr	2-qtr	1-qtr	2-qtr
rev_t	-0.103*	-0.186**	-0.029**	-0.017**
[t]	[-1.68]	[-2.07]	[-2.16]	[-1.97]
σ_t^{rev}	0.181*	0.307**	0.010	0.007
[t]	[1.68]	[2.24]	[0.45]	[0.27]
N	148	147	150	149
	Forecasting Investment			
	Data		Model	
	1-qtr	2-qtr	1-qtr	2-qtr
$\widehat{\text{spr}}_{t+1}$	-0.287	-0.512*	-0.008*	0.004
[t]	[-1.04]	[-2.29]	[-1.80]	[0.37]
N	148	147	150	149

Figure A.1: Revisions in Investor Expectations of Corporate Profits (1970–2024)

(a) Mean Revisions



(b) Dispersion Across Forecasters



Note: This figure plots the current revision in next quarter's expected profit ($\text{rev}_t = \text{E}_t[\Pi_{t+1}] - \text{E}_{t-1}[\Pi_{t+1}]$) from the Survey of Professional Forecasters (SPF) as a fraction of current GDP. The left panel plots the mean level and the right panel shows the dispersion across individual forecasters. Shaded areas indicate NBER recession dates.