# Information Spreads*

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**Abstract**

We propose a financially-driven business cycle propagation mechanism in which firm credit spreads arise from default concerns under incomplete information. Investors learn from public information and adjust expectations about firm creditworthiness downward in response to a deterioration in the profit outlook or increase in uncertainty. 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 level and variation of credit spreads and the patterns in responding 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

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# 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, actual default risks appear incapable of reconciling the high levels and variation of spreads observed (Collin-Dufresn, Goldstein, and Martin, 2001; Driessen, 2005; Gilchrist and Zakrajšek, 2012). Nor can standard business cycle models reproduce these patterns without quantitatively implausible costs of default. 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?

This paper develops and evaluates exactly such a mechanism and its macro implications. We explain credit spreads as arising from default concerns under incomplete information, but within an environment of rational and risk-neutral agents. Ceteris paribus, noise in the information about firm profitability increases the dispersion of the distribution. Although our lenders are risk neutral, at any given interest rate, debt payments are concave in profitability when default is a possibility and repayment is generally high. Uncertainty therefore lowers expected debt payments and the value of debt. Informative signals of future profitability, whether firm-specific or aggregate, are therefore informative of the price of debt, and we show that spreads correspondingly respond to shocks to both the mean and dispersion of these signals. Theoretically, we develop this idea 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 this mechanism. Quantitatively, we show that model simulations reproduce these regression results, again at both the aggregate and firm-level. Finally, the model establishes a novel amplification mechanism whereby credit spreads transmit changes in public information and its uncertainty to investment and exacerbates aggregate volatility.

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. These impacts are persistence, 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 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 forecasts) 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, and default 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 countercyclical. By contrast, credit spreads are much lower and counterfactually pro-cyclical 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, welfare counterfactuals based on firm value and investment point to large distortions from imperfect information. 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.[1] This literature has struggled to simultaneously match spreads and default data, especially given reasonable costs of default. [2]. 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.

[1] 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.

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

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, and Terry, 2019; and Greenwood, Hanson, and Jin, 2019).[3] To empirically support 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).

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.

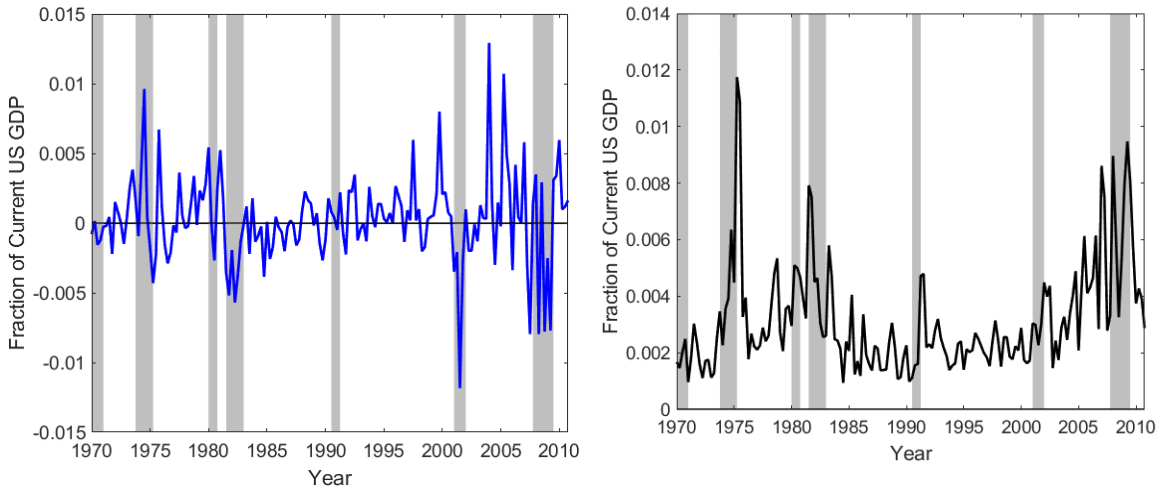
## 2 Empirical Evidence

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

[3]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 (FIRE), 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.

of our mechanism and provides evidence on the causal relationship of the signals on spreads and real outcomes.

## 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 $\sigma_t^{\text{rev}}$. Figure 1 presents the quarterly aggregate data between 1973 and 2010.[4] Both revisions and their dispersion display considerable fluctuations around business-cycle turning points, with revisions dipping and their dispersion spiking markedly in downturns.

[4]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, we show in the appendix that 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 |
|---|---|---|---|---|---|
| $\text{rev}_t$ | -0.103* | -0.186** | -0.129** | -0.124* | -0.057 |
| [t] | [-1.68] | [-2.07] | [-2.04] | [-1.68] | [-1.47] |
| $\sigma_t^{\text{rev}}$ | 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 $\text{spr}_{t+k}$ 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 $\text{rev}_t$ and $\sigma_t^{\text{rev}}$ 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 $\sigma_t$. 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 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 $\Delta y_{t+k}$ is, in turn, the $k$-quarter ahead cumulative investment and output growth, with $k = 1, 2, 3, 4, 8$ respectively.[5] $\widehat{\text{spr}}_{t+1}$ is the one-quarter ahead predicted spread from the forecasting regression (1) using both our measure of expectations of corporate profits $\text{rev}_t$ and its dispersion $\sigma_t^{\text{rev}}$. 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

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

**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.

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 average 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.[6]

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, $\sigma_{it}^{\text{rev}}$, as the dispersion (standard deviation) of revisions across individual forecasters at $t$.[7] As explained below, we also consider a residualized version of $\text{rev}_{it}$, which is constructed as the analyst-specific component that is estimated after controlling for the firm-specific component of $\text{rev}_{it}$. 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

[6]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).

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

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 $\text{rev}_{it}$ and $\sigma_{it}^{\text{rev}}$), spread ($\text{spr}_{it+k}$) and investment growth ($\Delta y_{t+k}$), while controlling for firm-level lagged spread, firm size and profitability, and time fixed effects $\tau_t$:

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

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

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 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 $t$.[8] 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.

[8]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).

**Table 3:** Cross-Sectional Correlations from Micro Data

| Panel A: Expectations and Credit Spreads | | | | | |
|---|---|---|---|---|---|
| | 1-qtr | 2-qtr | 3-qtr | 4-qtr | 8-qtr |
| $\text{rev}_{it}$ | -0.056*** | -0.050*** | -0.037*** | -0.037*** | 0.024 |
| [t] | [-8.17] | [-6.57] | [-4.31] | [-3.55] | [1.31] |
| $\sigma_{it}^{\text{rev}}$ | 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.

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 $\text{rev}_{jit}$ is the change in expectations for firm $i$ in quarter $t$ by analyst $j$. $\alpha_{it}$ is a firm-quarter fixed effect.[9] $\text{Analyst}_{jit}$ 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 the firm-level shocks, $\varepsilon_{it}^{\text{rev}}$, i.e.

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

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.

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 $\tau_t$ denotes time fixed effects. The results are reported in Panel A of Table 4. The negative (positive) relation between changes in expectations

[9]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.

**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 $\text{rev}_{it}$, $\varepsilon_{it}^{\text{rev}}$, 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.

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 $\text{IV}_{it}$ 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 funda-

mentals. Specifically, we use a dummy variable $\text{merger}_{it}$ that is equal to one if a firm $i$ was covered by two brokerage houses that merged before $t$, and zero otherwise. In Panel B of Table 4, we report the results from 2SLS using both $\text{merger}_{it}$ 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),[10] 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.8). 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.

[10]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 |
| $\widehat{rev}_{it}$ | -0.043*** | -0.043*** | -0.030*** | -0.037*** | 0.021 |
| [t] | [-6.11] | [-5.61] | [-3.52] | [-3.44] | [1.13] |
| $\widehat{\sigma}_{it}^{rev}$ | 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 |
| $\widehat{rev}_{it}$ | -0.014*** | -0.011*** | -0.010*** | -0.001 | 0.004 |
| [t] | [-7.86] | [-4.75] | [-3.36] | [-0.47] | [0.81] |
| $\widehat{\sigma}_{it}^{rev}$ | 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, $\sigma_t^{\text{rev}}$, 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 $\text{rev}_t$ and $\sigma_t^{\text{rev}}$ 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.9, these proxies remain highly significant for forecasting credit spreads both in the aggregate and at the firm level.

# 3 Model

We next develop a model to examine the quantitative importance of imperfect information in credit markets. This is a dynamic model of optimal financial and investment policy for heterogeneous firms facing financial and information frictions. Firms can borrow only state-uncontingent (long-term) debt to finance investment and are allowed to default on their debt. The main novelty of the model lies in the information structure. We consider three different information structures – asymmetric information, imperfect information, and full information – and calibrate each version of the model separately. Below we present the asymmetric information model as our baseline, where lenders cannot observe some latent state of the firm; instead, they form beliefs about it based on a noisy, publicly-available signal. Thus the price of defaultable bond reflects lenders' subjective probability of firm default. We relegate the exposition of the other model variants to Appendix C.

## 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 $\eta_{jt}$ that is i.i.d. over time and across firms:

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

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 $\delta$ is the rate of depreciation. The purchase of new capital is subject to quadratic adjustment costs:

$$g(k_{jt}, k_{jt+1}) = \frac{c_k}{2} \Big( \frac{k_{jt+1} - (1 - \delta) k_{jt}}{k_{jt}} \Big)^2 k_{jt}. \tag{15}$$

where $c_k$ determines the slope of the marginal adjustment cost.

### B. Information Frictions

In the baseline model, we assume asymmetric information between firms and lenders. In Appendix C, we present an alternative model with symmetric but imperfect information, where neither firms nor lenders can distinguish $z_t$ from $\eta_{jt}$ in $a_t$ (e.g. Lorenzoni, 2009). In the asymmetric information version, we assume that firms have full information, and while lenders observe $a_{jt}$, they cannot distinguish $z_t$ and $\eta_{jt}$ in $a_{jt}$. Instead, lenders receive a noisy public signal $s_t$ related to the contemporaneous com-

ponent $\varepsilon_t^z$ of the aggregate productivity process:

$$s_t = \varepsilon_t^z + u_t, \tag{16}$$

where $u_t$ denotes the noise in the signal, which prevents agents from perfectly identifying the aggregate shock $\varepsilon_t^z$. Moreover, $u_t$ is i.i.d. normal and has a time-varying noise $\sigma_{ut}^2$ that is also i.i.d. normal; in other words, $u_t \sim N(0, \sigma_{ut}^2)$ and $\sigma_{ut} \sim N(0, \omega_{\sigma_u}^2)$. $\varepsilon_t^z$, $\eta_{jt}$, $u_t$ and $\sigma_{ut}$ are mutually uncorrelated. Let

$$\Omega_{jt} = \left\{a_{jt}, s_t, \sigma_{ut}, a_{jt-1}, s_{t-1}, \sigma_{ut-1}, ..., a_{j0}, s_0, \sigma_{u0}\right\} \tag{17}$$

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 $\Omega_{jt}$.

### 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 $\lambda$ 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 borrowing limit, i.e. the maximum amount of new debt a firm can raise, given the current bond price schedule, $q(b_{jt+1}, k_{jt+1}, \Omega_{jt})$:

$$M(b_{jt}, \Omega_{jt}) = \max_{b_{jt+1}, k_{jt+1}} q(b_{jt+1}, k_{jt+1}, \Omega_{jt}) \left(b_{jt+1} - (1-\lambda)b_{jt}\right) \tag{18}$$

Firms pay their equity holders their revenues net of production costs, investment, tax

and debt payments, and face a non-negative payout condition:

$$
\begin{aligned}
e_{jt} &\equiv e(z_t, \eta_{jt}, k_{jt}, b_{jt}, k_{jt+1}, b_{jt+1}, \Omega_{jt}) \\
&= \underbrace{(1-\tau)\big(\exp(z_t+\eta_{jt})k_{jt}^{\alpha} - f\big)}_{\text{after-tax profit}} - \underbrace{(c+\lambda)b_{jt}}_{\text{debt repayment}} + \underbrace{q(b_{jt+1}, k_{jt+1}, \Omega_{jt})\Big(b_{jt+1} - (1-\lambda)b_{jt}\Big)}_{\text{new debt issues}} \\
&\quad - \underbrace{\big(k_{jt+1} - (1-\delta)k_{jt}\big) - g\big(k_{jt}, k_{jt+1}\big) + \tau\big(\delta k_{jt} + c b_{jt}\big)}_{\text{investment, adj. cost, and tax rebate}} \geq 0, \qquad (19)
\end{aligned}
$$

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

From (19), one can define the cutoff level of the idiosyncratic shock $\eta^*_{jt+1}$, which satisfies:

$$
\begin{aligned}
\eta^*_{jt+1} \equiv& \eta^*(z_{t+1}, k_{jt+1}, b_{jt+1}, k_{jt+2}, \Omega_{jt+1}) \qquad (20) \\
=& \log\Bigg[\Bigg(\frac{1}{1-\tau}\Big[k_{jt+2} - (1-\delta)k_{jt+1} + g\big(k_{jt+1}, k_{jt+2}\big) + (c+\lambda)b_{jt+1} \\
& - \tau\big(\delta k_{jt+1} + c b_{jt+1}\big) - M(b_{jt+1}, \Omega_{jt+1})\Big] + f\Bigg)k_{jt+1}^{-\alpha}\Bigg] - z_{t+1}.
\end{aligned}
$$

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. If default happens, the value of the firm becomes zero, and creditors can seize a fraction $1-\xi \in [0,1)$ of the firm's undepreciated capital, $(1-\delta)k_{jt+1}$ while continuing to hold the remaining debt, $(1-\lambda)b_{jt+1}$. For tractability, we assume that the current shareholders of the firm walk away, and new shareholders take over in the same period, so the firm resumes operating.

## 3.2 Debt Market Equilibrium

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

$$q(b_{jt+1},k_{jt+1},\Omega_{jt}) = \beta \times \Bigg[ \iiint \Big(1 - \Phi\big(\eta^*(z_{t+1},k_{jt+1},b_{jt+1},k_{jt+2},\Omega_{jt+1})\big)\Big) \times \underbrace{\Big[c + \lambda + (1-\lambda)q\big(b_{jt+2},k_{jt+2},\Omega_{jt+1}\big)\Big]}_{\text{no default payoff}} d\widetilde{F}(z_{t+1}|\Omega_{jt}) dG(s_{jt+1}|\sigma_{ut+1}) dH(\sigma_{ut+1}) + \iiiint_{\eta_{jt+1}<\eta^*(z_{t+1},k_{jt+1},b_{jt+1},k_{jt+2},\Omega_{jt+1})} \underbrace{B(b_{jt+1},k_{jt+1},b_{jt+2},k_{jt+2},z_{t+1},\Omega_{jt+1})}_{\text{default payoff}} \times d\Phi(\eta_{jt+1}) d\widetilde{F}(z_{t+1}|\Omega_{jt}) dG(s_{jt+1}|\sigma_{jt}) dH(\sigma_{jt+1}) \Bigg] \tag{21}$$

where $B(b_{jt+1},k_{jt+1},b_{jt+2},k_{jt+2},z_{t+1},\Omega_{jt+1}) =$

$$\Big((1-\xi)(1-\delta)k_{jt+1} + (1-\lambda)q\big(b_{jt+2},k_{jt+2},\Omega_{jt+1}\big)b_{jt+1}\Big)\frac{1}{b_{jt+1}} \tag{22}$$

gives the recovery rate, and $\xi \in (0,1]$ denotes the deadweight loss in default (Townsend, 1979). Importantly, $\widetilde{F}(z_{t+1}|\Omega_{jt})$ denotes the perceived distribution of $z_{t+1}$, conditional on observing the history $\Omega_{jt+1}$. This does not necessarily reflect the true distribution conditional on $z_t$, $F(z_{t+1}|z_t)$. Since investors cannot observe the true state $z_t$, the price of debt is computed conditional on the history $\Omega_{jt+1}$ instead of $z_t$.[11] Investors continuously update their perceived distribution $\widetilde{F}(z_{t+1}|\Omega_{jt})$, as new information arrives in each period.

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):

$$\text{spr}(b_{jt+1},k_{jt+1},\Omega_{jt}) = \frac{c + \lambda + (1-\lambda)\widetilde{\text{E}}[q(b_{jt+2},k_{jt+2},\Omega_{jt+1})|\Omega_{jt}]}{q(b_{jt+1},k_{jt+1},\Omega_{jt})} - (c+1), \tag{23}$$

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

[11] In the asymmetric information case, we assume that information on precisely how $\{b_{jt+1},k_{jt+1}\}$ depend on $z_t$ is too costly for individual lenders to acquire; in other words, investors cannot infer $z_t$ by inverting firms' policy functions. Such assumption is not required in the (symmetric) imperfect information model (see Appendix C).

### 3.3 Firm's Problem

Now we formalize firm $j$'s problem recursively. Let $V(k_{jt}, b_{jt}, z_t, \eta_{jt}, \Omega_{jt})$ denote the value of firm $j$ after all shocks are realized in period $t$. The value of a defaulting firm is

$$V(k_{jt}, b_{jt}, z_t, \eta_{jt}, \Omega_{jt}) = 0, \tag{24}$$

i.e. if it cannot satisfy the nonnegative equity payout condition (19). Non-defaulting firms choose new capital $k_{t+1}$, debt $b_{jt+1}$, and equity payouts $e_{jt}$ to solve:

$$V(k_{jt}, b_{jt}, \eta_{jt}, z_t, \Omega_{jt}) = \max_{b_{jt+1}, k_{jt+1}, e_{jt}} \left\{ e_{jt} + \beta \left[ \iiiint_{\eta_{jt+1} \geq \eta^*(z_{t+1}, k_{jt+1}, b_{jt+1}, k_{jt+2}, \Omega_{jt+1})} \right. \right. \tag{25}$$

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

subject to the nonnegative equity payout condition (19), the bond pricing function (**??**), default threshold (20), and the evolution of $z_{t+1}$ (12) and $\Omega_{jt+1}$ (17). In the asymmetric information case, since firms do observe the aggregate state $z_t$, they use the true (conditional) distribution of $z_{t+1}$, denoted by $F(z_{t+1}|z_t)$, to compute expectations. Nonetheless, since the bond price enters the definition of equity payout, the history $\Omega_{jt}$ remains a state vector for the firm.

## 4 Quantitative Analysis

In this section, we first discuss the calibration of the model, followed by an outline of the algorithm and a comparison of moments in the model and the data.

### 4.1 Parameterization

We solve and calibrate three variants of the model: the asymmetric information (AI) model (Section 3), the imperfect information (II) model (Appendix C.1), and the full information (FI) model (Appendix C.2).

Each model is calibrated 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. Then we jointly calibrate the rest of parameters to target firm-level moments.

The externally calibrated parameters are: $\{\alpha, \delta, \beta, \tau, c, \lambda, \rho_z, \sigma_\varepsilon, \omega_{\sigma_u}\}$. 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).[12] The quarterly depreciation rate $\delta$ is 0.025. The rate of time preference $\beta = 0.99$ implies an annualized risk-free rate of 4%. The effective corporate tax rate $\tau$ is 30%, in line with the evidence in Graham (2000). The next parameter is the periodic coupon rate $c$. We set it equal to $\frac{1}{\beta} - 1$, so that the price of default-free debt is one.

The next four parameters $\{\lambda, \rho_z, \sigma_\varepsilon, \omega_{\sigma_u}\}$ are calibrated according to their natural data counterpart. We set $\lambda$ 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, $\rho_z$ and $\sigma_\varepsilon$, govern the dynamics of firms' revenues, and we fit an AR(1) to the data on sales-to-asset from the quarterly Compustat database. 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 $\varepsilon_t^z$ in each period plus some noise $u_t$ (see equation 16). 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, $\sigma_{ut}$ (Figure A.2). Then we compute the standard deviation of this series and use this to calibrate $\omega_{\sigma_u}$.

The last four parameters $\{c_k, \sigma_\eta, f, \xi\}$ are jointly calibrated to target firm-level moments, which are the mean and standard deviation of default rate, the mean investment rate, and the mean leverage. 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 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 investment rate is largely affected by the investment adjustment cost $c_k$. The mean leverage is affected by the bankruptcy cost $\xi$. The mean and standard deviation of default rate are jointly

[12] 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.

**Table 6:** Parameterization

| Parameter | Description | AI | II | FI |
|---|---|---|---|---|
| *Preferences and technology* | | | | |
| $\alpha$ | Returns to scale | 0.65 | 0.65 | 0.65 |
| $\delta$ | Depreciation rate | 0.025 | 0.025 | 0.025 |
| $\beta$ | Time preference | 0.99 | 0.99 | 0.99 |
| $\sigma_\eta$ | Std dev idiosyncratic shock | 0.0105 | 0.0109 | 0.0106 |
| $\tau$ | Corporate tax rate | 0.3 | 0.3 | 0.3 |
| $c_k$ | Investment adjust. cost | 0.156 | 0.143 | 0.152 |
| $\rho_z$ | Aggregate shock persistence | 0.93 | 0.93 | 0.93 |
| $\sigma_\varepsilon$ | Std dev aggregate shock | 0.0095 | 0.0095 | 0.0095 |
| $f$ | Fixed cost | 0.162 | 0.151 | 0.174 |
| *External financing* | | | | |
| $\xi$ | Bankrupty cost | 0.36 | 0.31 | 0.39 |
| $c$ | Coupon rate | 0.0101 | 0.0101 | 0.0101 |
| $\lambda$ | Debt amortization rate | 0.05 | 0.05 | 0.05 |
| $\omega_{\sigma u}$ | Std dev of noise in signal | 0.0043 | 0.0043 | 0.0043 |

affected by the fixed cost $f$ and the standard deviation of idiosyncratic TFP $\sigma_\eta$. The parameters in each model are reported in Table 6.

## 4.2 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 (25) and the bond pricing schedule (21) requires computing the conditional density function $\tilde{f}(z_{t+1}|\Omega_{jt})$ using

$$z_{t+1}|\Omega_{jt} \sim N\Big(\rho_z z_{t|t}, \Theta_{t+1|t}\Big),$$

where $\rho_z z_{t|t}$ and $\Theta_{t+1|t}$ denote the conditional mean and variance, respectively. Recall that the observables at $t$, $\Omega_{jt}$, include the history of $a_{jt}$, $s_t$, and $\sigma_{ut}$.

We obtain these estimates for each quarter in 1985Q1-2010Q4, using an expanding window of survey data from 1970Q1 to 2010Q4. After obtaining the time series for $(z_{t|t}, \Theta_{t|t})$, we discretize the states $(z_{t|t}, \Theta_{t+1|t}, s_t, \sigma_{ut})$ and approximate $\tilde{f}(z_{t+1}|\Omega_t)$ using transition matrix $\widehat{\Pi}_z(z_{t+1}\Big|z_{t|t}, \Theta_{t+1|t})$. Thus, we can approximate the firm states as $(k_{jt}, b_{jt}, \eta_{jt}, z_{t|t}, \Theta_{t+1|t})$; in other words, we do not need to keep track of the entire

**Table 7:** Moment Matching Exercise

| | Data | AI | II | FI |
|---|---|---|---|---|
| **Targeted Moments** | | | | |
| Investment (mean) | 0.018 | 0.019 | 0.020 | 0.019 |
| Leverage (mean) | 0.267 | 0.272 | 0.268 | 0.270 |
| Default rate (mean) | 0.013 | 0.011 | 0.010 | 0.012 |
| Default rate (std) | 0.012 | 0.009 | 0.007 | 0.010 |
| **Untargeted Moments** | | | | |
| Bond spread (mean) | 0.019 | 0.017 | 0.014 | 0.009 |
| $\sigma$(spread) | 0.011 | 0.010 | 0.008 | 0.010 |
| Corr(spread, output) | -0.573 | -0.392 | -0.127 | 0.043 |
| Corr(default, output) | -0.431 | -0.214 | -0.113 | 0.065 |
| Corr(leverage,output) | 0.126 | 0.327 | 0.221 | 0.369 |
| $\sigma$(invest)/$\sigma$(output) | 3.458 | 2.482 | 2.213 | 2.336 |
| Corr(invest, output) | 0.574 | 0.891 | 0.875 | 0.908 |

history $\Omega_{jt}$.

## 4.3 Model Fit

Table 7 summarizes the model predictions of the aggregate moments and their data counterparts. Panel A presents the targeted moments, and Panel B shows the non-targeted moments for credit spreads, defaults, and investment. Both asymmetric and imperfect information models can capture the countercyclical default rates and credit spreads, and generate a reasonable level of spread with a realistic level of default rate and risk-neutral preferences.

Models with information frictions generate higher credit spreads on average because when investors are uncertain about a low probability event (default), they attach more weight to it. The intuition is as follows. The firm's default probability matters for the price of bond because there is deadweight loss in default. In the full information case, the price of bond depends on the firm's true default probability, conditional on observing $z_t$. In Figure A.3, we plot the distribution of $z_{t+1}$ conditional on $z_t$ (solid line), and the area to the left of the threshold $z^*$ denotes the default probability. If investors observe $s_t$ instead of $z_t$, the price of bond depends on the distribution of $z_{t+1}$ conditional on $s_t$ (dotted line). Importantly, the distribution of $z_{t+1}$ conditional on $s_t$ has a fatter tail than the distribution conditional on $z_t$, as the conditional variance is greater. Therefore, for any default threshold $z^*$ less than $z_t$ (i.e. default is a low probability event), the area under the dashed line is greater than the area under the

solid line; in other words, investors' subjective belief of the firm's default probability is larger than the actual default probability. Therefore, in addition to the "default premium," models with imperfect information also features an "uncertainty premium," resulting in higher average spreads.

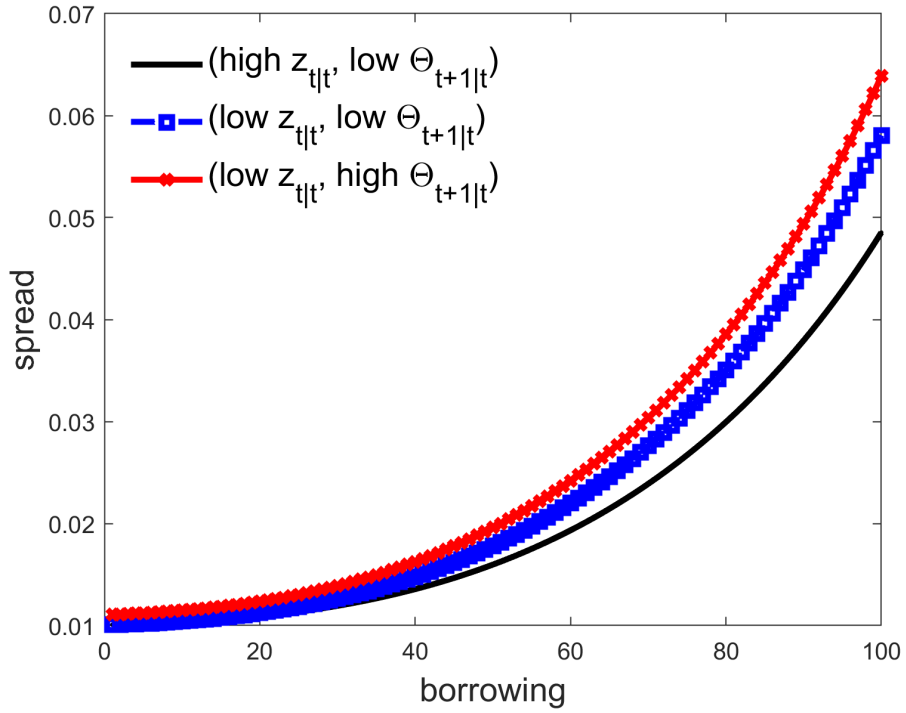
Moreover, the model can generate countercyclical spreads without imposing time-varying default costs or other types of aggregate shocks. This largely reflects the fact that the signals are more volatile than the fundamentals, so the shifts in credit supply have a larger impact on the equilibrium credit spreads. In workhorse real business cycle (RBC) model with defaultable debt, empirically plausible parameterization often leads to procyclical credit spreads. This result runs counter to the data, as discussed by Gomes, Yaron, and Zhang (2003), and Gilchrist, Sim, and Zakrajšek (2014). The procyclical behavior of credit spreads in the model arises because an adverse technology shock induces firms to deleverage as there are fewer profitable investment opportunities. A reduction in borrowing leads to an improvement in the firm's credit worthiness – or equivalently, a reduction in default probability – thus lowering the credit spread. We illustrate this intuition in Panel (a) of Figure A.4: with fewer investment opportunities, the firm's demand for credit is lower at every price level. As a result, the bond market equilibrium shifts down. Since the spread schedule is upward sloping, the new equilibrium features a counterfactually lower spread in an economic downturn.

Panel (b) of Figure A.4 shows the bond market equilibrium in a model with imperfect information. The difference is that now the spread schedule is also a function of the noisy signal. If signals are procyclical, then the spread schedule shifts upward in a recession: with a lower $s_t$, $\text{spr}_t$ is higher at every level of $b_{t+1}$. Moreover, if signals are noisier during recessions, the spread schedule shifts up further. Since the signals are noisy, their movements do not coincide with the movements in fundamentals. If the signals are more pessimistic than the actual decline in fundamentals (such as in the 2007-09 financial crisis), the shift in spread dominates the shift in demand, which leads to countercyclical credit spreads. As such the mechanism can generate large shifts in credit supply that originate from information frictions in debt markets.

## 4.4 Bond Pricing Schedules

Now we assess the impact of information frictions through the policy functions in the asymmetric information model. Figure 2 shows the spread levels at different levels of debt, for different values of conditional mean and variance $(z_{t|t}, \Theta_{t+1|t})$. At each level of debt, the combination of low $z_{t|t}$ (due to receiving bad signals) and high $\Theta_{t+1|t}$ (due to receiving noisy signals) generates the highest level of spread. The combination of

**Figure 2:** Credit Spread Schedules




bad and noisy signals is what we saw during the 2007-09 financial crisis (see Figure 1).

Figure 3 shows the firm's optimal borrowing, and the equilibrium credit spread, i.e. the level of spread given the optimal level of borrowing. Recall that in the asymmetric information model, $z_{t|t}$ and $\Theta_{t+1|t}$) are also firm states as the price of bond enters the firm's equity (19). Figure 3 considers two scenarios: when the perceived state $z_{t|t}$ and the actual state $z_t$ coincide (green), and when the perceived state is worse than the actual state (red). The left panel of figure 3 shows that firms tend to borrow more when the perceived state is worse than the actual state, as the firm knows the true state. Higher borrowing drives up the default premium, as shown in the right panel. Moreover, since investors perceive the state to be worse than it is, they demand a higher premium than under full information.

Finally, we show in Figure 4 that noise has nonlinear impact on credit spread. To this end, we plot the spread schedule at different levels of the conditional variance $\Theta_{t+1|t}$ and different levels of existing debt. Two observations stand out. First, credit spread is increasing in noise variance until a "threshold" level $\widehat{\Theta}_{t+1|t}$. Noise generates uncertainty, and lenders demand a higher premium to compensate for the uncertainty. However, when the variance is too high, signals are too imprecise and agents tend to discard them. Thus, intermediate levels of noise variance generate the highest level of spread. Second, the impact of noise is stronger when firms are highly leveraged. This

**Figure 3:** Decision Rules

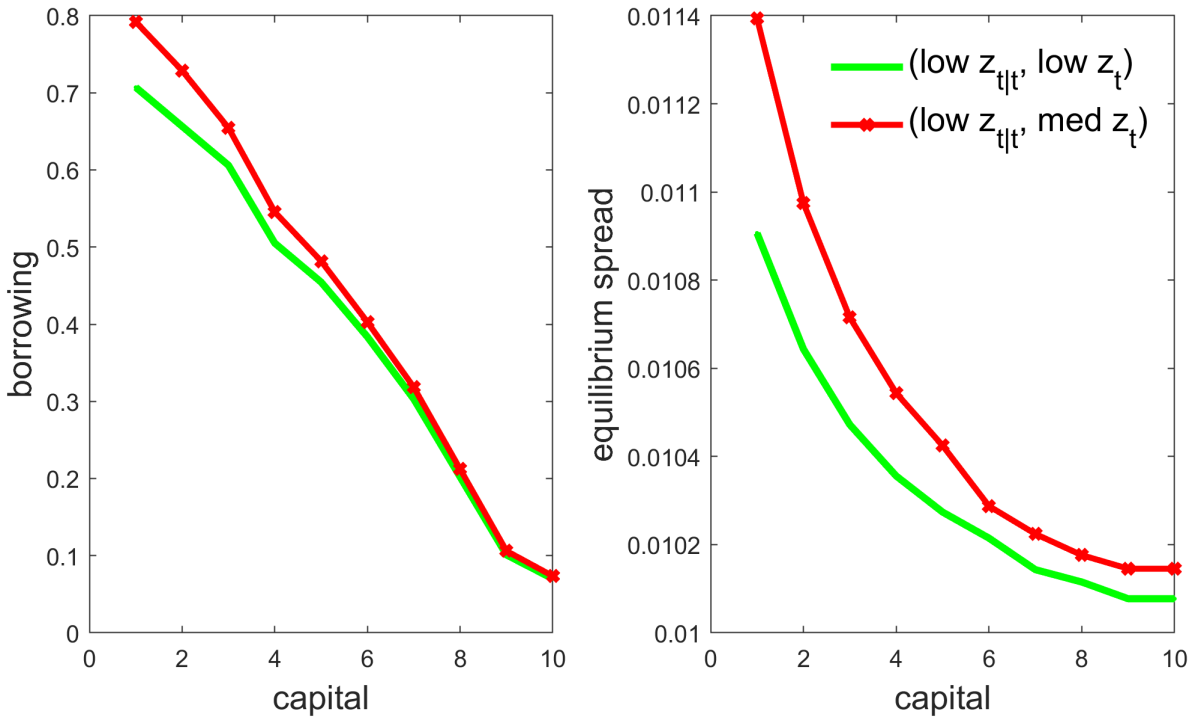
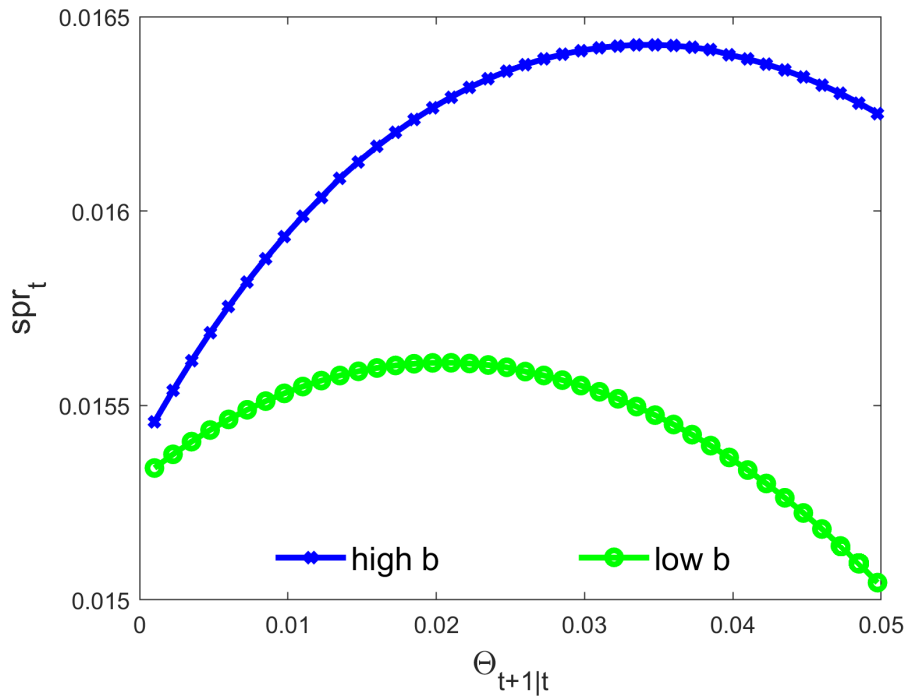



**Figure 4:** Nonlinear Impact of Noise on Spread



highlights an interaction effect of financial and information frictions: when the default risk is high, the impact of imperfect information is amplified.

## 4.5 Credit Cycles

We examine the extent to which each model generates credit cycles in two ways. First, we compare the model-implied credit spread to the actual data (Figure 5), by feeding into the model the realized profitability shocks and signals (revisions) from the data. Second, we repeat the forecasting regressions using the model-implied spread from this exercise.

In this exercise, we use the full sample (1970Q1-2010Q4) of revision series and its dispersion to obtain $(z_{t|t}, \Theta_{t+1|t})$ for 1985Q1-2010Q4. Then we feed them into the model, along with the time series for $z_t$ and randomly drawn $\eta_{jt}$. We compute the average bond spread (at each $t$) in each model, and plot them in Figure 5. Both the asymmetric information and the imperfect information models generate countercyclical spread, with the asymmetric information model being closer to the data.

As an additional test for model fit, we repeat our empirical exercise in Section 2 using the model-implied credit spread shown in Figure 5. To maintain comparability with our empirical analysis, we adopt a time series regression for the same sample period, using the average spread across firms. We include current TFP ($z_t$), investment, and lagged spread as control variables in the model-implied regressions. Table 8 summarizes the results in each model. Our information proxies have significant forecasting power for the model-implied spread in both the asymmetric and imperfect information models, while they are insignificant in the full information model after controlling for the current fundamental.

**Figure 5:** Historical Bond Spread: Data vs. Model

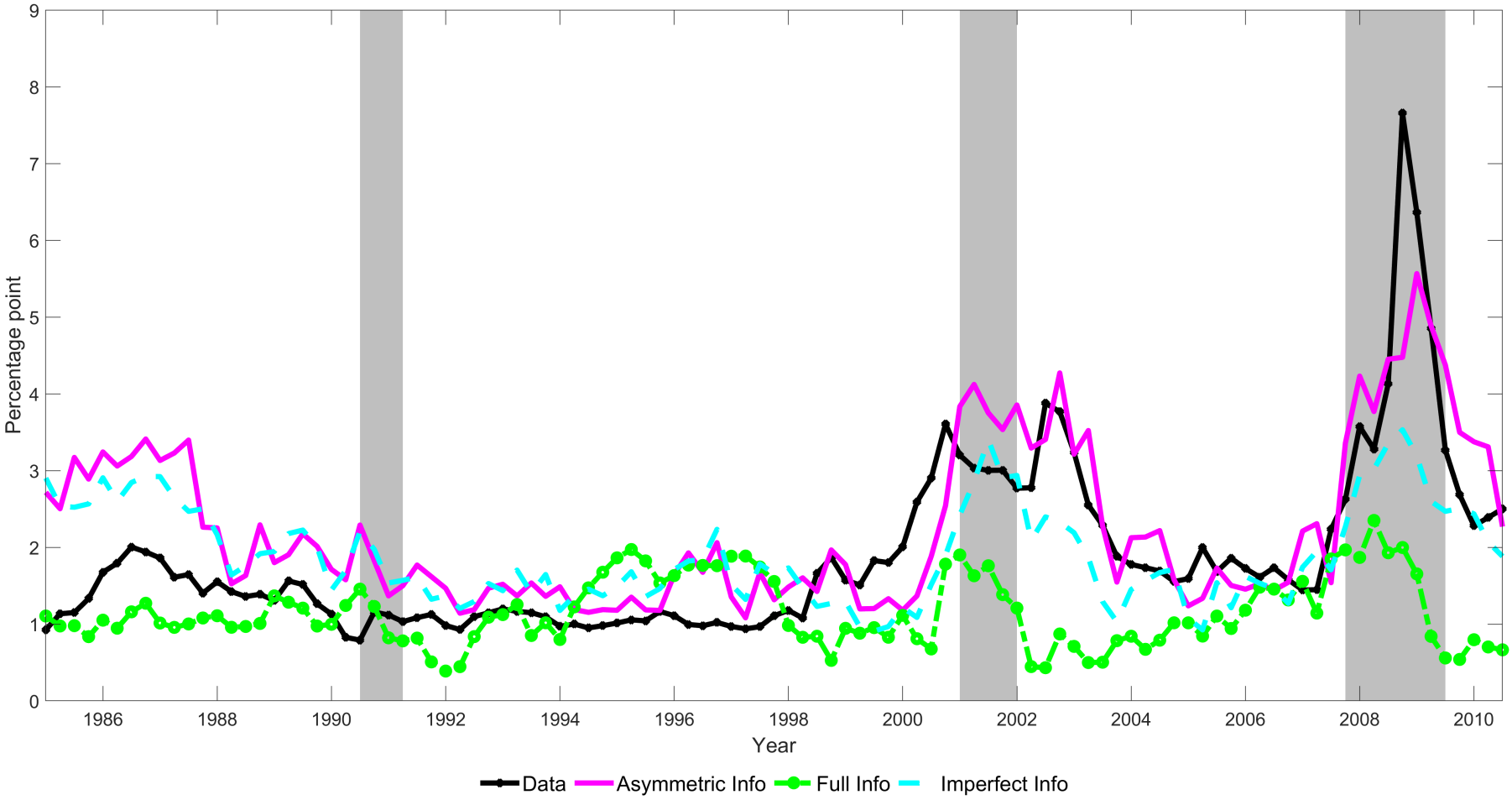


**Table 8:** Model-Implied Regressions

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

| | 1-qtr | 2-qtr | 3-qtr | 4-qtr | 8-qtr |
|---|---|---|---|---|---|
| **AI** | | | | | |
| $\text{rev}_t$ | -0.072*** | -0.066*** | -0.061*** | -0.052** | -0.021 |
| [t] | [5.963] | [3.275] | [2.566] | [2.381] | [1.284] |
| $\sigma_t^{\text{rev}}$ | 0.083** | 0.076** | 0.064* | 0.051* | 0.047 |
| [t] | [2.853] | [2.392] | [1.788] | [1.709] | [1.487] |
| $z_t$ | 0.012** | 0.008** | 0.006* | 0.005* | 0.003 |
| [t] | [2.426] | [2.108] | [1.853] | [1.734] | [1.161] |
| **II** | | | | | |
| $\text{rev}_t$ | -0.063*** | -0.056*** | -0.053** | -0.045* | -0.015 |
| [t] | [4.715] | [3.277] | [2.585] | [1.856] | [1.230] |
| $\sigma_t^{\text{rev}}$ | 0.032** | 0.029** | 0.024* | 0.021 | 0.016 |
| [t] | [2.461] | [2.245] | [1.786] | [1.305] | [1.159] |
| $z_t$ | 0.003 | 0.003 | 0.002 | 0.002 | 0.001 |
| [t] | [1.380] | [1.129] | [1.011] | [0.917] | [0.779] |
| **FI** | | | | | |
| $\text{rev}_t$ | 0.002 | -0.003 | -0.002 | 0.001 | -0.001 |
| [t] | [0.483] | [0.429] | [0.325] | [0.258] | [0.189] |
| $\sigma_t^{\text{rev}}$ | 0.001 | 0.001 | -0.003 | -0.002 | -0.001 |
| [t] | [0.362] | [0.365] | [0.363] | [0.283] | [0.194] |
| $z_t$ | 0.009*** | 0.007*** | 0.005** | 0.003* | 0.002* |
| [t] | [4.607] | [4.402] | [2.439] | [1.823] | [1.793] |

# 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.

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# Information Spreads (Online Appendix)

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## 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 $\varepsilon_t^z$, 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 $u_t$, $\sigma_{ut}^2$, in equation (16).

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 (16); in other words, the average signal across forecasters here is the public signal in the dynamic model. Furthermore, the variance of the aggregate noise $\sigma_{ut}^2$ 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 ($\sigma_{ut}$).

# B Computation

## B.1. Estimating the firm's latent state using data on revisions

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 (16) 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:

$$x_{jt} = C\alpha_{t-1} + \zeta_t \tag{A.3}$$

where

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

$\varepsilon_t^z$, $u_t$ and $\eta_{jt}$ 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 $z_{t|t}$ and $\Theta_{t|t}$ denote the estimated conditional mean and variance. Thus, we find $z_{t|t}$ and $\Theta_{t|t}$ for each quarter in 1985Q1-2010Q4 using an expanding window of the revision series ($s_t$) and its dispersion ($\sigma_{ut}$) 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 Alternative Models

## C.1. (Symmetrically) Imperfect Information Model

In this case, neither firms nor lenders can distinguish $z_t$ from $a_{jt}$. As a result, firm value is now given by:

$$V(k_{jt}, b_{jt}, \eta_{jt}, \Omega_{jt}) = \max_{b_{jt+1}, k_{jt+1}, e_{jt}} \left\{ e_{jt} + \beta \left[ \iiiint_{\eta_{jt+1} \geq \eta^*(z_{t+1}, k_{jt+1}, b_{jt+1}, k_{jt+2}, \Omega_{jt+1})} \right. \right. \tag{A.4}$$
$$\left. \left. V(k_{jt+1}, b_{jt+1}, \eta_{jt+1}, z_{t+1}, \Omega_{jt+1}) d\Phi(\eta_{jt+1}) d\widetilde{F}(z_{t+1}|\Omega_{jt}) dG(s_{t+1}|\sigma_{ut+1}) dH(\sigma_{ut+1}) \right] \right\},$$

subject to the nonnegative equity payout condition (19), the bond pricing function (**??**), default threshold (20), and the evolution of $\Omega_{jt+1}$ (17). The rest of the model is the the same as in the asymmetric information case.

## C.2. Full Information Model

This is the closest to existing firm financing models under full information (e.g. Gilchrist, Sim, and Zakrajšek, 2014, Arellano, Bai, and Kehoe, 2019, Gomes and Schmid, 2020). All agents can perfectly distinguish $z_t$ from $a_{jt}$. As a result, the bond pricing schedule is a function of $z_t$, $q(b_{jt+1}, k_{jt+1}, z_t)$. The maximum borrowing limit is now given by:

$$M(b_{jt}, z_t) = \max_{b_{jt+1}, k_{jt+1}} q(b_{jt+1}, k_{jt+1}, z_t)(b_{jt+1} - (1-\delta)b_{jt}), \tag{A.5}$$

and firm equity is defined as:

$$\begin{aligned} e_{jt} &\equiv e(z_t, \eta_{jt}, k_{jt}, b_{jt}, k_{jt+1}, b_{jt+1}) \\ &= \underbrace{(1-\tau)\left(\exp(z_t + \eta_{jt}) k_{jt}^{\alpha} - f\right)}_{\text{after-tax profit}} - \underbrace{(c+\lambda) b_{jt}}_{\text{debt repayment}} + \underbrace{q(b_{jt+1}, k_{jt+1}, z_t)\left(b_{jt+1} - (1-\lambda) b_{jt}\right)}_{\text{new debt issues}} \\ &\quad - \underbrace{\left(k_{jt+1} - (1-\delta) k_{jt}\right) - g\left(k_{jt}, k_{jt+1}\right) + \tau\left(\delta k_{jt} + c b_{jt}\right)}_{\text{investment, adj. cost, and tax rebate}} \geq 0. \end{aligned} \tag{A.6}$$

From the non-negative equity condition one can back out the cutoff level of idiosyncratic shock:

$$\begin{aligned}\eta^*_{jt+1} \equiv & \eta^*(z_{t+1}, k_{jt+1}, b_{jt+1}, k_{jt+2}) \\ = & \log\left[\left(\frac{1}{1-\tau}\Big[k_{jt+2} - (1-\delta)k_{jt+1} + g\big(k_{jt+1}, k_{jt+2}\big) + (c+\lambda)b_{jt+1} \right.\right. \\ & \left.\left. - \tau\big(\delta k_{jt+1} + c b_{jt+1}\big) - M(b_{jt+1}, z_{t+1})\Big] + f\right) k_{jt+1}^{-\alpha}\right] - z_{t+1}.\end{aligned} \tag{A.7}$$

We use this in the bond pricing schedule, which satisfies the break-even condition:

$$\begin{aligned}& q(b_{jt+1}, k_{jt+1}, z_t) = \beta \times \\ & \left[\int \Big(1 - \Phi\big(\eta^*(z_{t+1}, k_{jt+1}, b_{jt+1}, k_{jt+2})\big)\Big) \underbrace{\Big[c + \lambda + (1-\lambda) q\big(b_{jt+2}, k_{jt+2}, z_{t+1}\big)\Big]}_{\text{no default payoff}} dF(z_{t+1}|z_t) \right. \\ & \left. + \iint_{\eta_{jt+1} < \eta^*(z_{t+1}, k_{jt+1}, b_{jt+1}, k_{jt+2})} \underbrace{B(b_{jt+1}, k_{jt+1}, b_{jt+2}, k_{jt+2}, z_{t+1})}_{\text{default payoff}} d\Phi(\eta_{jt+1}) dF(z_{t+1}|z_t)\right],\end{aligned} \tag{A.8}$$

where the recovery rate is $B(b_{jt+1}, k_{jt+1}, b_{jt+2}, k_{jt+2}, z_{t+1}) =$

$$\Big((1-\xi)(1-\delta)k_{jt+1} + (1-\lambda) q\big(b_{jt+2}, k_{jt+2}, z_{t+1}\big) b_{jt+1}\Big) \frac{1}{b_{jt+1}}. \tag{A.9}$$

Finally, the firm's problem is given by:

$$\begin{aligned}V(k_{jt}, b_{jt}, \eta_{jt}, z_t) = \max_{b_{jt+1}, k_{jt+1}, e_{jt}} & \left\{ e_{jt} + \beta \left[ \iint_{\eta_{jt+1} \geq \eta^*(z_{t+1}, k_{jt+1}, b_{jt+1}, k_{jt+2})} \right.\right. \\ & \left.\left. V(k_{jt+1}, b_{jt+1}, \eta_{jt+1}, z_{t+1}) d\Phi(\eta_{jt+1}) dF(z_{t+1}|z_t) \right] \right\}\end{aligned} \tag{A.10}$$

subject to the nonnegative equity payout condition (A.6), the bond pricing function (A.8), default threshold (A.7), and the evolution of $z_{t+1}$ (12).

# D Two Period Model

Here we construct a simple partial-equilibrium example to illustrate our mechanism in its starkest and most intuitive form. To focus on how imperfect information about the firm's default probability affects the pricing of bonds, we assume here that there

is a one-period risky bond, an exogenous default threshold, and a fixed level of credit demand from the firm. All these features are relaxed in our model.

Consider the pricing of a one-period risky corporate bond $b_{t+1}$ whose payoff in $t+1$ is given by:

$$x_{t+1} = \begin{cases} R_t & \text{if } z_{t+1} \geq z^* \\ 0 & \text{if } z_{t+1} < z^* \end{cases} \tag{A.11}$$

where $z_{t+1}$ indicates the firm's profit in the next period, and $z^*$ is the default threshold. For simplicity, in this section we assume that $z^*$ is exogenous. The price of bond is determined before the realization of $z_{t+1}$, which follows the process:

$$z_{t+1} = z_t + \sigma_\varepsilon \varepsilon_{t+1}, \quad \varepsilon_{t+1} \sim N(0,1).$$

Risk-neutral lenders demand a constant expected return of 1, so the spread is equal to $R_t - 1$. If lenders can observe $z_t$, they use the conditional distribution $z_{t+1}|z_t \sim N(z_t, \sigma_\varepsilon^2)$ to price the bond in period $t$:

$$q_t = \beta \Big[ 1 - \Phi\Big( \frac{z^* - z_t}{\sigma_\varepsilon} \Big) \Big] \tag{A.12}$$

and credit spread is:

$$\text{spread}^{FI}(z_t) = R_t^{FI} - 1 = \Phi\Big( \frac{z^* - z_t}{\sigma_\varepsilon} \Big) \Big[ 1 - \Phi\Big( \frac{z^* - z_t}{\sigma_\varepsilon} \Big) \Big]^{-1} \tag{A.13}$$

where $\Phi(\cdot)$ is the c.d.f. of a standard normal distribution. This is the full information case.

Now suppose investors cannot observe $z_t$, but they know that $z_t$ is normally distributed with mean $\bar{z}$ and variance $\sigma_z^2$. In each period, they observe a "signal" $s_t$, which is a linear function of $z_t$ and an iid noise $u_t$:

$$s_t = z_t + \sigma_u u_t, \quad u_t \sim N(0,1),$$

where $z_t$, $\varepsilon_t$ and $u_t$ are independent. After observing $s_t$, investors can compute the conditional distribution of $z_{t+1}$:

$$z_{t+1}|s_t \sim \Big( \bar{z} + \frac{\sigma_z^2}{\sigma_z^2 + \sigma_u^2}(s_t - \bar{z}), \quad \sigma_z^2 + \sigma_\varepsilon^2 - \frac{(\sigma_z^2)^2}{\sigma_z^2 + \sigma_u^2} \Big),$$

and use this to price the bond:

$$\tilde{q}_t = \beta\left[1 - \Phi\left(\frac{z^* - \bar{z} - \frac{\sigma_z^2}{\sigma_z^2+\sigma_u^2}\left(s_t - \bar{z}\right)}{\sqrt{\sigma_z^2 + \sigma_\varepsilon^2 - \frac{(\sigma_z^2)^2}{\sigma_z^2+\sigma_u^2}}}\right)\right], \tag{A.14}$$

and credit spread is:

$$\text{spread}^{II}(s_t) = \Phi\left(\frac{z^* - \bar{z} - \frac{\sigma_z^2}{\sigma_z^2+\sigma_u^2}\left(s_t - \bar{z}\right)}{\sqrt{\sigma_z^2 + \sigma_\varepsilon^2 - \frac{(\sigma_z^2)^2}{\sigma_z^2+\sigma_u^2}}}\right)\left[1 - \Phi\left(\frac{z^* - \bar{z} - \frac{\sigma_z^2}{\sigma_z^2+\sigma_u^2}\left(s_t - \bar{z}\right)}{\sqrt{\sigma_z^2 + \sigma_\varepsilon^2 - \frac{(\sigma_z^2)^2}{\sigma_z^2+\sigma_u^2}}}\right)\right]^{-1}. \tag{A.15}$$

This equation represents the investors' demand for bonds under imperfect information. The first result is immediate:

**Lemma 1.** *The higher the observed signal $s_t$, the lower the spread$_t^{II}$.*

*Proof.* It is immediate from equation (A.14) that:

$$\frac{\partial \tilde{q}_t}{\partial s_t} = -\beta\phi\left(\frac{z^* - \bar{z} - \frac{\sigma_z^2}{\sigma_z^2+\sigma_u^2}\left(s_t - \bar{z}\right)}{\sqrt{\sigma_z^2 + \sigma_\varepsilon^2 - \frac{(\sigma_z^2)^2}{\sigma_z^2+\sigma_u^2}}}\right)\frac{-\frac{\sigma_z^2}{\sigma_z^2+\sigma_u^2}}{\sqrt{\sigma_z^2 + \sigma_\varepsilon^2 - \frac{(\sigma_z^2)^2}{\sigma_z^2+\sigma_u^2}}}$$

where $\phi(\cdot)$ is the p.d.f. of a standard normal distribution. Therefore, $\frac{\partial \tilde{q}_t}{\partial s_t} > 0$. ■

The second observation from (A.15) relates the spread to the precision of the signal:

**Lemma 2.** *When the default threshold is $z^*$ sufficiently low, the higher the variance of noise $\sigma_u^2$, the higher the spread$_t^{II}$.*

*Proof.* Let

$$A \equiv \left(\frac{z^* - \bar{z} - \frac{\sigma_z^2}{\sigma_z^2+\sigma_u^2}\left(s_t - \bar{z}\right)}{\sqrt{\sigma_z^2 + \sigma_\varepsilon^2 - \frac{(\sigma_z^2)^2}{\sigma_z^2+\sigma_u^2}}}\right)$$

so equation (A.14) becomes $\tilde{q}_t = \beta\Big[1 - \Phi\big(A\big)\Big]$. We can show that:

$$\begin{aligned}
\frac{\partial A}{\partial \sigma_u^2} =& \sigma_z^2(\sigma_z^2+\sigma_u^2)^{-2}(s_t-\bar{z})\Big(\sigma_z^2+\sigma_\varepsilon^2-\frac{(\sigma_z^2)^2}{\sigma_z^2+\sigma_u^2}\Big)^{-\frac{1}{2}} \\
&+\Big(z^*-\bar{z}-\frac{\sigma_z^2}{\sigma_z^2+\sigma_u^2}(s_t-\bar{z})\Big)\Big(-\frac{1}{2}\Big)\Big(\sigma_z^2+\sigma_\varepsilon^2-\frac{(\sigma_z^2)^2}{\sigma_z^2+\sigma_u^2}\Big)^{-\frac{3}{2}}(\sigma_z^2)^2\Big(\sigma_z^2+\sigma_u^2\Big)^{-2} \\
=& \sigma_z^2(\sigma_z^2+\sigma_u^2)^{-2}\Big(\sigma_z^2+\sigma_\varepsilon^2-\frac{(\sigma_z^2)^2}{\sigma_z^2+\sigma_u^2}\Big)^{-\frac{1}{2}} \\
&\Bigg[s_t-\bar{z}-\frac{1}{2}\Big(z^*-\bar{z}-\frac{\sigma_z^2}{\sigma_z^2+\sigma_u^2}(s_t-\bar{z})\Big)\Big(\sigma_z^2+\sigma_\varepsilon^2-\frac{(\sigma_z^2)^2}{\sigma_z^2+\sigma_u^2}\Big)^{-1}\sigma_z^2\Bigg].
\end{aligned}$$

If the default threshold $z^*$ is sufficiently low:

$$\begin{aligned}
z^* &< 2\big(s_t-\bar{z}\big)\Big(\sigma_z^2+\sigma_\varepsilon^2-\frac{(\sigma_z^2)^2}{\sigma_z^2+\sigma_u^2}\Big)\sigma_z^{-2}+\frac{\sigma_z^2}{\sigma_z^2+\sigma_u^2}\big(s_t-\bar{z}\big)+\bar{z} \\
z^* &< \big(s_t-\bar{z}\big)\left[\frac{2(\sigma_z^2+\sigma_\varepsilon^2)}{\sigma_z^2}-\frac{\sigma_z^2}{\sigma_z^2+\sigma_u^2}\right]+\bar{z}.
\end{aligned}$$

then $\frac{\partial A}{\partial \sigma_u^2} > 0$, and $\frac{\partial \tilde{q}_t}{\partial \sigma_u^2} < 0$. ■

Intuitively, having a sufficiently low default threshold implies that default is a low probability event. We verify this in our quantitative model. The third observation concerns the relation between spread$^{FI}$ and spread$^{II}$. To facilitate comparison, we assume that the realized $z_t$ and $s_t$ are equal to the unconditional mean, i.e. $z_t = \bar{z}$ and $s_t = \bar{z}$. Then the mean of $z_{t+1}$ conditional on $z_t$ is the same as the mean of $z_{t+1}$ conditional on $s_t$, which is $\bar{z}$. Then, from equations (A.13) and (A.15), we see that:

**Lemma 3.** *The spread under imperfect information is higher than the spread under full information when the default threshold $z^*$ is sufficiently low, i.e. spread$_t^{II}$ > spread$_t^{FI}$ for all $z^* < \bar{z}$.*

*Proof.* Suppose that $z_t = \bar{z}$ and $s_t = \bar{z}$, then the bond pricing equations become:

$$q_t = \beta\Big[1-\Phi\Big(\frac{z^*-\bar{z}}{\sigma_\varepsilon}\Big)\Big] \tag{A.16}$$

$$\tilde{q}_t = \beta\left[1-\Phi\left(\frac{z^*-\bar{z}}{\sqrt{\sigma_z^2+\sigma_\varepsilon^2-\frac{(\sigma_z^2)^2}{\sigma_z^2+\sigma_u^2}}}\right)\right] \tag{A.17}$$

for the full information and imperfect information cases, respectively. Since

$$\left(\sigma_z^2+\sigma_\varepsilon^2-\frac{(\sigma_z^2)^2}{\sigma_z^2+\sigma_u^2}\right)-\sigma_\varepsilon^2=\frac{\sigma_z^2\sigma_u^2}{\sigma_z^2+\sigma_u^2}>0 \quad \Leftrightarrow \quad \left(\sigma_z^2+\sigma_\varepsilon^2-\frac{(\sigma_z^2)^2}{\sigma_z^2+\sigma_u^2}\right)>\sigma_\varepsilon^2$$

then

$$\Phi\left(\frac{z^*-\bar{z}}{\sqrt{\sigma_z^2+\sigma_\varepsilon^2-\frac{(\sigma_z^2)^2}{\sigma_z^2+\sigma_u^2}}}\right) \;>\; \Phi\Big(\frac{z^*-\bar{z}}{\sigma_\varepsilon}\Big) \quad \text{for all } \; z^*<\bar{z}.$$

Therefore, $\tilde{q}_t$ in (A.17) is smaller than $q_t$ in (A.16), for all $z^*<\bar{z}$. ■

**Table A.1:** Summary Statistics of Aggregate Data

| Panel A: Expectations of Corporate Profits, Aggregate Level | | | | | |
|---|---|---|---|---|---|
| Year | $\text{rev}_t$ | $\sigma_t^{\text{rev}}$ | Year | $\text{rev}_t$ | $\sigma_t^{\text{rev}}$ |
| 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, $\text{rev}_t$, 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, $\sigma_t^{\text{rev}}$, 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 |
| $\text{rev}_{it}$ | -0.79 | 1.00 | -5.55 | 1.67 |
| $\varepsilon_{it}^{\text{rev}}$ | 0.02 | 1.00 | -3.28 | 3.21 |
| $\sigma_{it}^{\text{rev}}$ | 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 |
| $\text{Spread}_{it}$ | 1.70 | 2.25 | -2.20 | 13.19 |
| Observations | | 189,507 | | |
| Bonds | | 4,963 | | |
| Firms | | 775 | | |
| $\text{Capex growth}_{it}$ | -0.13 | 1.92 | -6.76 | 5.36 |
| $\text{Total assets}_{it}$ ($ billion) | 10.42 | 13.95 | 0.29 | 58.28 |
| $\text{ROA}_{it}$ | 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, $\text{rev}_{it}$, 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 $\text{rev}_{it}$, Shock to $\text{rev}_{it}$ ($\varepsilon_{it}^{\text{rev}}$), 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 |
| $\text{rev}_t$ | -0.195** | -0.209** | -0.107 | -0.069 | -0.022 |
| [t] | [-2.21] | [-2.03] | [-1.19] | [-0.70] | [-0.44] |
| $\sigma_t^{\text{rev}}$ | 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 |
| $\text{rev}_t$ | -0.165** | -0.173** | -0.121 | -0.081 | 0.014 |
| [t] | [-2.11] | [-1.83] | [-1.40] | [-1.02] | [0.25] |
| $\sigma_t^{\text{rev}}$ | 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 $\Gamma X_{t-1}$). $t$-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 $\text{rev}_{it}$ 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 $\text{rev}_{it}$, $\varepsilon_{it}^{\text{rev}}$, 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:** 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 $rev_{it}$, $\varepsilon_{it}^{rev}$, 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.

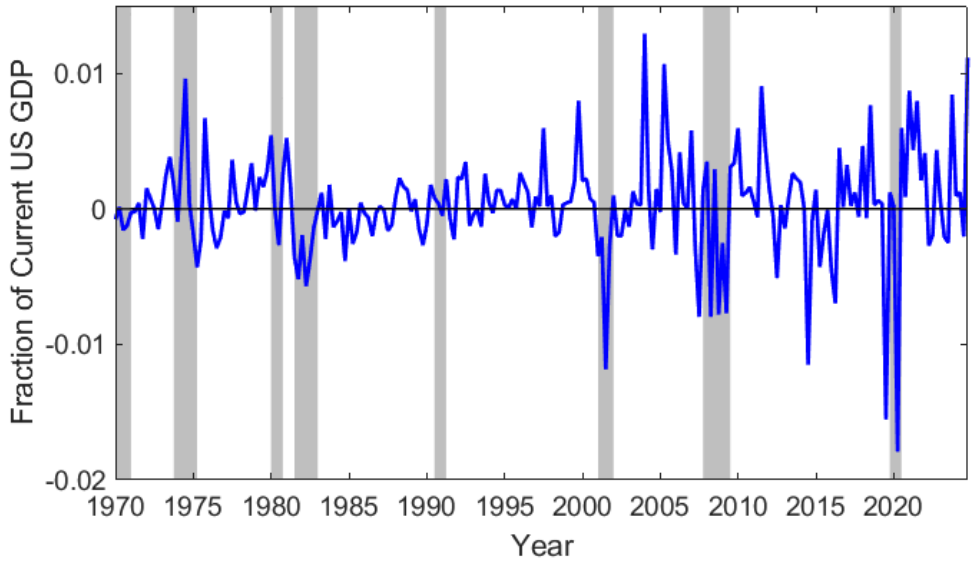
**Table A.9:** Credit Spreads and Forecast Errors

| | 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] |
| $\sigma_t^{FE}$ | 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] |
| $\sigma_{it}^{FE}$ | 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 |

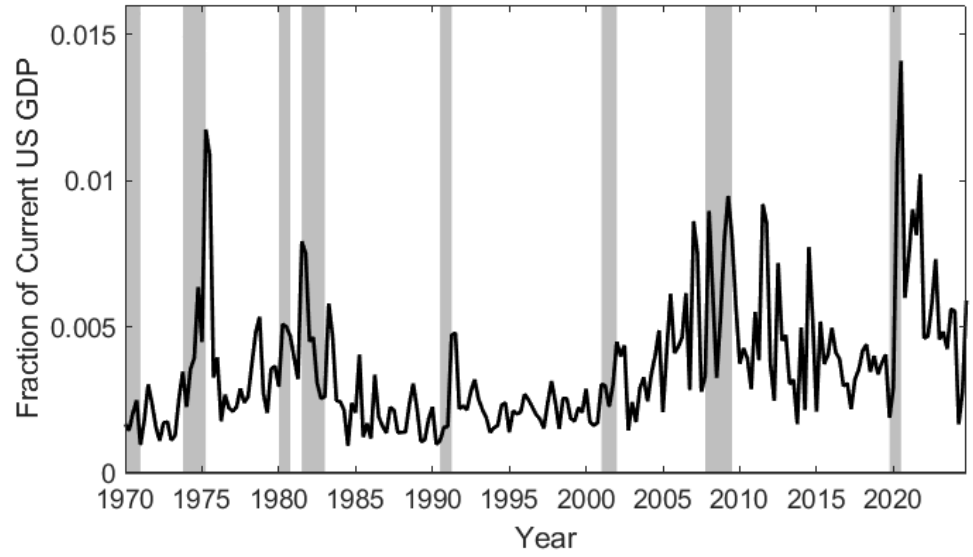
**Note**: This table summarizes the results of time-series forecasting regressions of corporate bond spreads on forecast errors of corporate profits and its dispersion. Forecast errors are defined as forecasts minus realized corporate profits. Panel A presents the regression results using aggregate data (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.

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

**(a)** Mean Revisions

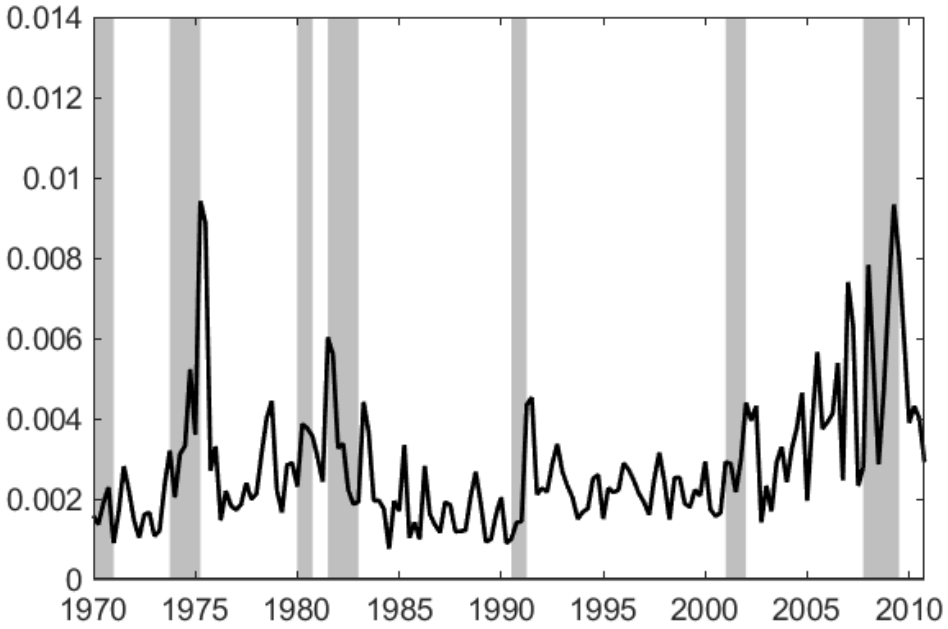



**(b)** Dispersion Across Forecasters




**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.

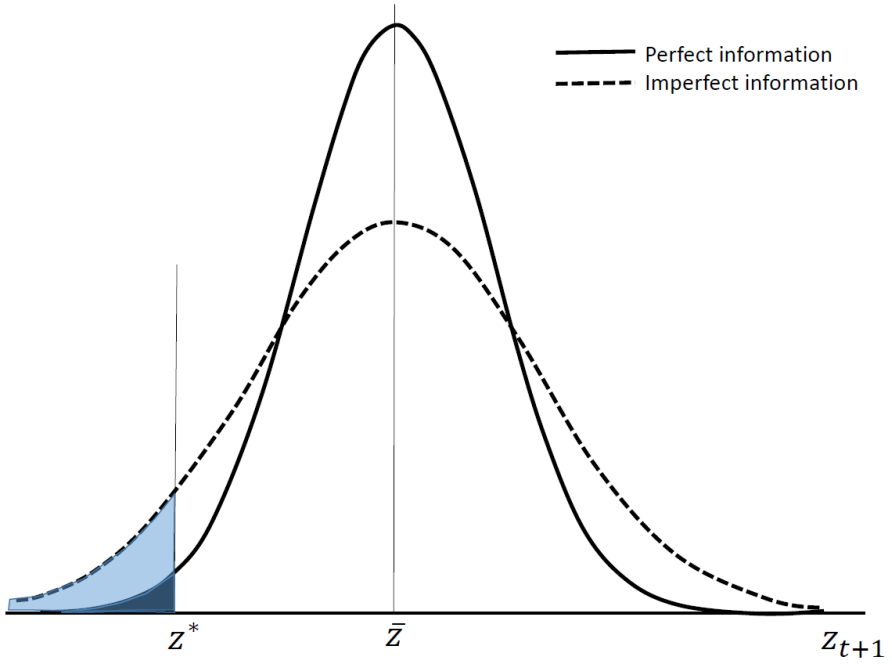
**Figure A.2:** Time-Varying Noise $\sigma_{ut}$ in the Model




**Note**: This figure plots the calibrated values of $\sigma_{ut}$ in the model. We first compute individual forecasters' current revision in next quarter's expected profit ($\text{rev}_t = \text{E}_t[\Pi_{t+1}] - \text{E}_{t-1}[\Pi_{t+1}]$) as a fraction of total non-financial assets held by U.S. non-financial corporate businesses. Then we compute the dispersion across forecasters for each quarter. Shaded areas indicate NBER recession dates.

**Figure A.3:** Imperfect Information and Estimated Default Probability

**(a)** Perfect vs. imperfect information




**(b)** Impact of signal under imperfect information

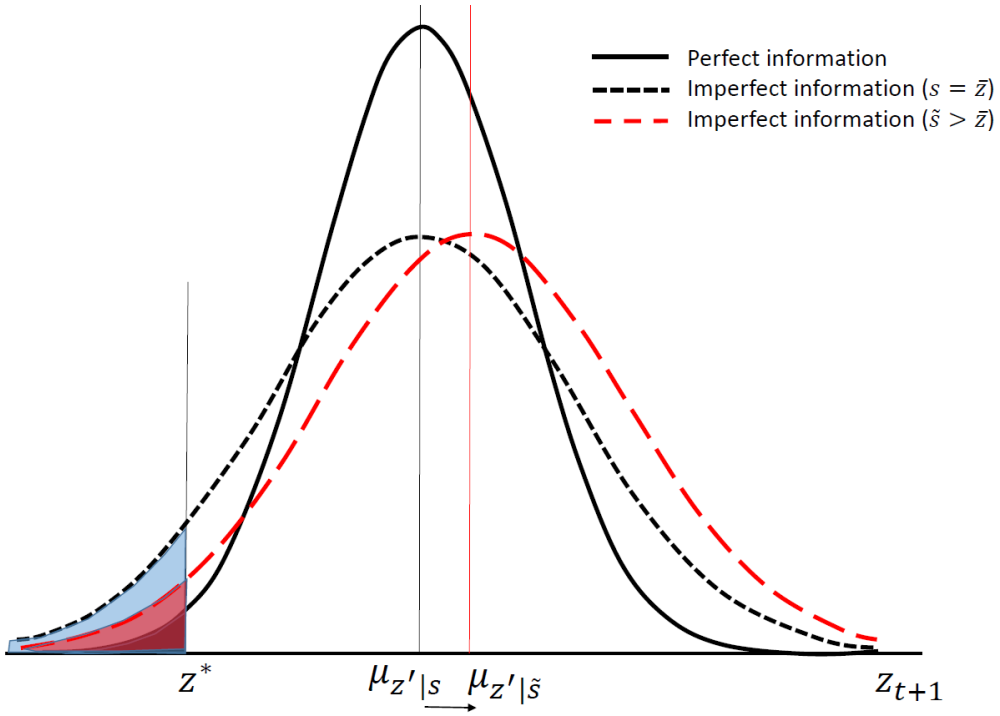
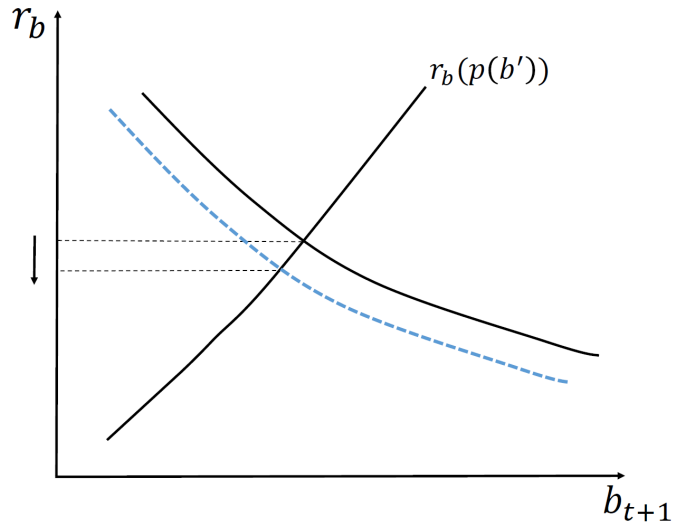


**Figure A.4:** Bond Market Equilibrium

**(a)** Full information model




**(b)** Model with imperfect information

