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 credit spreads remain an important amplifier for investment dynamics and aggregate volatility.

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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). However, standard business cycle models are unable to reconcile the high levels of spreads on bonds with empirically plausible default rates, much less the variation in spreads (Collin-Dufresn, Goldstein, and Martin, 2001; Driessen, 2005). If we have a mechanism to explain the high level and variation of spreads, will these spreads still have a significant 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. Ceteris paribus, noise in the information about firm profitability increases the dispersion of the distribution. 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, we show that credit spreads indeed remain important for aggregate business cycle properties. Their countercyclical nature – resulting in a higher cost of investing during recessions – acts as an amplifying mechanism for investment dynamics 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 costly external financing. 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 pre-

dicting 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 increase spreads. An increase in uncertainty likewise decreases the expected returns given concave payoff functions from defaultable lending. In response to pessimistic shocks, the firm too cuts back investment. 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.

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. 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 expected risk premia in the corporate bond market (including the excess return on corporate bonds, the excess return on BAA-rated corporate bonds, and the corporate bond premium of Gilchrist and Zakrajšek, 2012), 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 show utilize two approaches to construct these exogenous "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 realized profits. 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, profitability, 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 counter-cyclical. 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 Our paper focuses on the link between credit markets and business cycles and is complementary to a large literature on the financial accelerator, starting from the workhorse models of Bernanke, Gertler, and Gilchrist (1999) and Carlstrom and Fuerst (1997). Our results are consistent with the notion that an increase in the external financing cost is associated with a contraction in the supply of credit. Cooley and Quadrini (2001) as well as more recent contributions by Gilchrist, Sim, and Zakrajšek (2014) and Arellano, Bai, and Kehoe (2018) enrich the literature on incomplete financial markets with default risk by incorporating persistent firm-level heterogeneity – a feature that is also present in our model.

Few business cycle studies consider long-term debt with default.[1] Some exceptions include Gomes, Jermann, and Schmid, 2016; Gomes and Schmid, 2020. In Gomes, Jermann, and Schmid (2016), firms issue nominal debt and face unanticipated inflation, yet the fluctuations in spreads remain very small. Gomes and Schmid (2020) assume Epstein-Zin preferences to generate large fluctuations in risk premia, and in turn, credit spreads.

We contribute to these literatures by introducing 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.[2] We show that the mechanism simultaneously explains

[1]Some studies on sovereign default have also considered long-term debt in equilibrium models (see, for example, Arellano and Ramanarayanan, 2012; Aguiar and Amador, 2013; Hatchondo, Martinez, and Sosa-Padilla, 2016). In these studies, the problem of a sovereign differs along several dimensions from the problem of a firm in our model. For instance, firms in our model have the ability to issue equity to reduce debt, while sovereigns do not have that choice.

[2]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 (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). Relative to the former, our credit-supply theory of the business cycle seeks to explain fluctuations in the supply of direct credit (bonds), which has become a significant source of financing for U.S.

the level and variation in spreads, with empirically plausible bond maturity, default, and recovery rates. Moreover, we do this without requiring fluctuations in risk premia. We highlight the predictability of credit spreads, and their causal impact on the business cycle.

Our paper also speaks to a 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. To the best of our knowledge, our paper is the first to develop a model of credit spreads based on noisy learning. 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).

2 Empirical Evidence

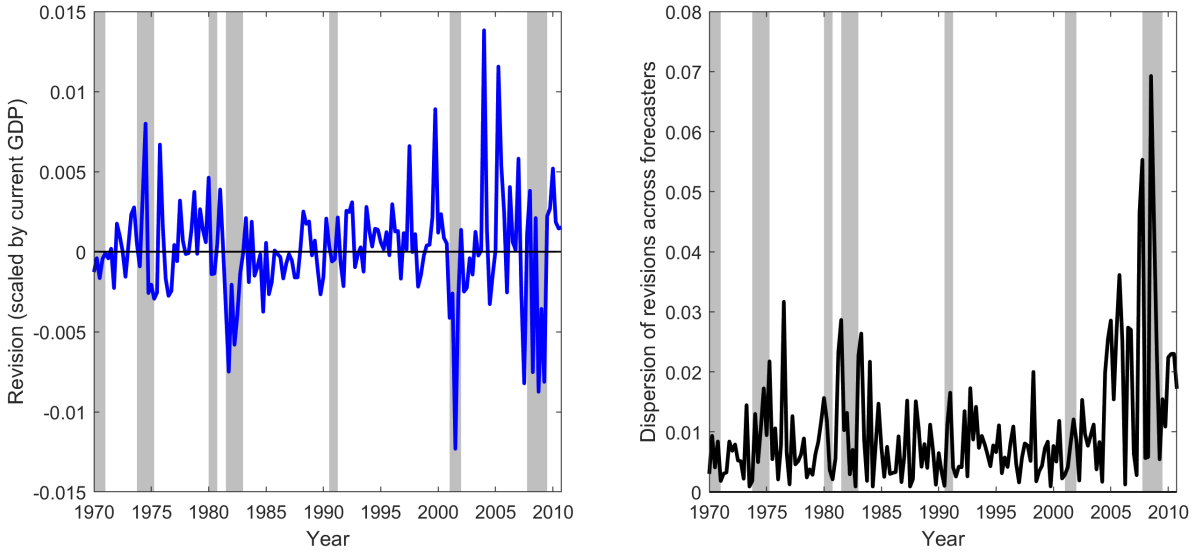
This section presents empirical evidence on the role of imperfect information in credit markets. We start with evidence from aggregate data, which is more relevant to our macro simulations, and then present micro evidence, which serves as a further test of our mechanism and provides evidence on the causal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

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 informa-

public firms (Adrian, Colla, and Shin, 2012; Benmelech, Kumar, and Rajan, 2019). Relative to the latter, bond prices in our model move in response to the arrival of noisy information, not just to changes in fundamentals.

Figure 1: Revisions in Investors' Expectations of Corporate Profits in the Aggregate



Note: This figure plots the variables of interest in our time-series regressions from the Survey of Professional Forecasters (SPF). The left panel plots the current revision in investors' expectations of next quarter corporate profits as a fraction of U.S. GDP. The right panel shows the standard deviation of revisions across individual forecasters.

tion. The second explanatory variable of interest is a measure of disagreement among forecasters about their beliefs. We use the dispersion (standard deviation) of revisions across individual forecasters, denoted σ_t^{rev}. Figure 1 presents the quarterly aggregate data between 1970 and 2010.

2.1.1 Expectations of Corporate Profits and Credit Spreads

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

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

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

Since the measures of expectations are scaled by their respective unconditional

Table 1: Aggregate Evidence on Forecasting Credit Spreads

	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
rev_t	-0.103*	-0.186**	-0.129**	-0.124*	-0.057
[t]	[-1.68]	[-2.07]	[-2.04]	[-1.68]	[-1.47]
σ_t^{rev}	0.181*	0.307**	0.476**	0.471***	0.469***
[t]	[1.68]	[2.24]	[2.15]	[2.65]	[3.43]
N	148	147	146	145	141
R^2	0.69	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.

standard deviation, we can interpret the coefficients in Table 1 as the change in credit spread (in percentage point) associated with a one standard deviation revision in expectations Rev_t, or its noise σ_t. For instance, a one standard deviation upward revision in investors' expectations lowers the GZ spread by about 10 basis points in the following quarter, whereas a one standard deviation increase in the dispersion of revisions raises the spreads by about 18 basis points, which are respectively about 6 percent and 10 percent of the unconditional mean of spreads in our sample (1.6 percentage points).

2.1.2 Expectations of Corporate Profits and the Business Cycle

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

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

where Δy_{t+k} is, in turn, the k-quarter ahead cumulative investment and output growth, with $k = 1,2,3,4,8$ respectively.[3] $\widehat{\text{spr}}_{t+1}$ is the one-quarter ahead predicted spread from

[3]In Appendix Table A.3, we present additional results where Δy_{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.

the forecasting regression (1) using both our measure of expectations of corporate profits rev_t and its dispersion σ_t^{rev}. As in the earlier regressions, we compute the t-statistics for k-period forecasting regressions based on Newey and West (1987) standard errors.

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

2.1.3 Economic Significance During the Financial Crisis

In summary, our aggregate evidence indicates that both deterioration in investor expectations of corporate profits and stronger disagreements about expectations tend to be followed by subsequent widening of credit spreads, and that the timing of this

widening is, in turn, closely tied to the onset of a contraction in economic activity. To provide an alternative assessment of economic significance, we consider the 2006 to 2008 period, when revisions were revised downward by about half of a standard deviation (44%), on average, and the dispersion of revisions increased by about 3 standard deviations (see Appendix Table A.1). Our first-stage estimates in Table 1 imply that the combined effect of downward revisions and higher dispersion raised spreads by about 60 basis points ($0.103 \times 0.44 + 0.181 \times 3$), on average, in that period.

Moreover, the combined magnitudes of the first and second stage estimates suggest that the impact of changes in investor expectations is economically meaningful also on the real side. Considering again the 2006 to 2008 period, our estimates imply that the combined effect of downward revisions and higher dispersion lowered investment and output by approximately 50 basis points (-0.819×-0.103×-0.44-0.819×0.181×3), on an 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.[4]

Using the detailed analyst-by-analyst forecasts, we calculate the firm-level consensus EPS forecast as the median of all analysts' forecasts for the relevant period. We then construct a quarterly measure of forecast revisions at the firm level that is analogous to our aggregate measure: $\text{rev}_{it} = \text{E}_t\left[\Pi_{i,t+1}\right] - \text{E}_{t-1}\left[\Pi_{i,t+1}\right]$, i.e., the firm-level measure is defined as the change between current and last period's forecasts of next quarter corporate profits of firm i at time t. Furthermore, we measure noise in investor expectations of corporate profits, σ_{it}^{rev}, as the dispersion (standard deviation) of revisions across individual forecasters at t.[5] As explained below, we also consider a residualized version of rev_{it}, which is constructed as the analyst-specific component that is estimated after controlling for the firm-specific component of rev_{it}. As in the aggregate data, we rescale the measures by their respective unconditional standard deviations to facilitate interpretation.

We then merge the firm-level measure of forecast revisions with monthly bond-level spreads from ICE/IDC for 1998-2010, which has comparable coverage to the formerly available Merrill Lynch database, and from the Warga database (via Mergent FISD) for 1982-1997. The IBES information is available starting from 1982, so the resulting samples are panels of about 5,000 bonds (800 firms) and 10,000 firms between 1982 and 2010, respectively. Appendix Table A.2 presents the summary statistics for the main variables.

2.2.2 Cross-Sectional Correlations

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

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

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

[4]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).

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

Table 3: Cross-Sectional Correlations from Micro Data

Panel A: Expectations and Credit Spreads					
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
rev_{it}	-0.056***	-0.050***	-0.037***	-0.037***	0.024
[t]	[-8.17]	[-6.57]	[-4.31]	[-3.55]	[1.31]
σ_{it}^{rev}	0.036***	0.054***	0.067***	0.088***	0.127***
[t]	[5.48]	[6.43]	[6.20]	[6.34]	[5.90]
Time FE	Yes	Yes	Yes	Yes	Yes
N	119,808	112,331	101,962	92,453	64,311
Bonds	4,218	3,991	3,817	3,609	3,007
Panel B: Predicted Spreads and Firm Investment					
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
$\widehat{\text{rev}}_{it}$	-0.618**	-0.686**	-0.585**	-0.720***	0.335
[t]	[-2.24]	[-2.46]	[-2.39]	[-2.64]	[1.10]
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, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

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. Second, we construct an instrument for the revisions, as the average of the analyst-time effects across the analysts who evaluated the firms, and we use this in reduced form regressions. This instrumented revision contains no firm-specific component other than the composition of the analysts at a point in time.

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

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

where rev_{jit} is the change in expectations for firm i in quarter t by analyst j. α_{it} is a firm-quarter fixed effect.[6] 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.

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

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 us-

[6]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.

ing two-stage least squares (2SLS):

$$\text{rev}_{it} = \zeta_0 + \zeta_1 \varepsilon_{it}^{\text{rev}} + \zeta_2 \sigma_{it}^{\varepsilon^{\text{rev}}} + \Gamma X_{it-1} + \tau_t + u_{it}, \tag{5}$$

$$\sigma_{it}^{\text{rev}} = \theta_0 + \theta_1 \varepsilon_{it}^{\text{rev}} + \theta_2 \sigma_{it}^{\varepsilon^{\text{rev}}} + \Gamma X_{it-1} + \tau_t + u_{it}, \tag{6}$$

$$\text{spr}_{it+k} = \alpha + \beta \widehat{\text{rev}}_{it} + \gamma \widehat{\sigma}_{it}^{\text{rev}} + \Gamma X_{it-1} + \tau_t + \varepsilon_{it+k}. \tag{7}$$

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

In addition, we augment the instrument set IV_{it} with one more instrument that exploits variation in revisions around 15 brokerage house mergers between 1982 and 2005 that affect over 500 firms for which we have complete information on revisions. The source of variation here, as documented by Hong and Kacperczyk (2010), is that these mergers reduce competition and lead to an increase in optimism bias for firms covered by both merging houses before the merger – i.e., they have a positive effect on revisions, which is plausibly unrelated to realized firm and macroeconomic fundamentals.[7] Specifically, we use a dummy variable 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 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,

[7]To ensure that we are not capturing just changes in analyst coverage, we exclude observations involving brokerage house closures, as these events have been shown to affect the information environment and the firm incentives to produce public information (see, for example, Balakrishnan, Billings, Kelly, and Ljungqvist, 2014).

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 5-7). In Panel A, the instruments are residualized rev_{it}, $\varepsilon_{it}^{\text{rev}}$, and its noise, $\sigma_{it}^{\varepsilon^{\text{rev}}}$. In Panel B, we use brokerage house mergers as an additional instrument. t-statistics are based on standard errors that are clustered at the bond level to allow for within-bond serial correlation, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

indicates that learning and behavioral biases are distinct and complementary mechanisms.

3 Mechanism

Before turning to our full model, 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. We use this simplified setting to highlight four findings that are central to our quantitative analysis.

3.1 The Level of Credit Spread

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

$$x_{t+1} = \begin{cases} R_t & \text{if } z_{t+1} \geq z^* \\ 0 & \text{if } z_{t+1} < z^* \end{cases} \tag{8}$$

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:

$$\text{spread}^{FI}(z_t) = R_t^{FI} - 1 = \Phi\Big(\frac{z^* - z_t}{\sigma_\varepsilon}\Big)\Big[1 - \Phi\Big(\frac{z^* - z_t}{\sigma_\varepsilon}\Big)\Big]^{-1} \tag{9}$$

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

Now suppose investors cannot observe z_t, but they know that z_t is normally distributed with mean $\bar{z}$ and variance σ_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, ε_t and u_t are independent. After observing s_t, investors can compute the conditional distribution of z_{t+1}:

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

and use this to price the bond:

$$\text{spread}^{II}(s_t) = \Phi\left(\frac{z^* - \bar{z} - \frac{\sigma_z^2}{\sigma_z^2+\sigma_u^2}\left(s_t-\bar{z}\right)}{\sqrt{\sigma_z^2+\sigma_\varepsilon^2 - \frac{(\sigma_z^2)^2}{\sigma_z^2+\sigma_u^2}}}\right)\left[1-\Phi\left(\frac{z^* - \bar{z} - \frac{\sigma_z^2}{\sigma_z^2+\sigma_u^2}\left(s_t-\bar{z}\right)}{\sqrt{\sigma_z^2+\sigma_\varepsilon^2 - \frac{(\sigma_z^2)^2}{\sigma_z^2+\sigma_u^2}}}\right)\right]^{-1}. \quad (10)$$

This equation represents the investors' demand for bonds under imperfect information. We highlight four key results by comparing this with the full information benchmark (9). The first observation is immediate:

1. The higher the observed signal s_t, the lower the spread_t^{II}.

The second observation from (10) relates the spread to the precision of the signal:

2. When the default threshold is z^* sufficiently low, the higher the variance of noise σ_u^2, the higher the spread_t^{II}.

Appendix A gives the upper bound of the default threshold z^* for this result to hold in this simplified model. 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 (9) and (10), we see that:

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

In our quantitative model, the mean of z_{t+1} conditional on z_t is not necessarily the same as the mean conditional on s_t in a period. Nonetheless, we show numerically that credit spreads are higher on average under imperfect information. Results 2 and

3 suggest an important interaction effect of financial and information frictions: when investors are uncertain about likelihood of default, a low probability event, they attach more weight to it. In other words, investors' subjective belief of the firm's default probability is larger than the actual default probability.

4 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. A firm can issue equity as well as defaultable debt to finance investment. Lenders know the structure of the economy but they cannot observe some latent state of the firm; instead, they form beliefs about it based on a noisy, publicly-available signal. This is the key innovation of the model. As a result, the defaultable bond issued by the firm is priced according to lenders' subjective beliefs. In what follows, we show that the interaction of financial and information frictions generates a novel amplification channel.

4.1 Economic Environment

A. Agents, Technology, and Income Processes

Time is discrete and the horizon infinite. There are continuums of firms and perfectly competitive lenders. A firm j produces output y_{jt} with decreasing returns to scale, $y_{jt} = \exp(z_t + \eta_{jt})k_{jt}^{\alpha}$, where $\alpha < 1$. k_t is the capital input, η_{jt} is an idiosyncratic revenue shock that is i.i.d. over time and across firms and $\eta_{jt} \sim iid\ N(0,\sigma_\eta^2)$. z_t is an aggregate shock that approximates the following autoregressive processes:

$$z_t = \rho_z z_{t-1} + \varepsilon_t^z \tag{11}$$

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:

$$\pi_{jt} = \exp(z_t + \eta_{jt})k_t^{\alpha} - f. \tag{12}$$

Capital accumulation follows:

$$k_{jt+1} = (1-\delta)k_{jt} + i_{jt}, \tag{13}$$

and δ is the rate of depreciation. The purchase of new capital is subject to quadratic adjustment costs:

$$g(k_{jt}, k_{jt+1}) = \frac{c_k}{2}\Big(\frac{k_{jt+1} - (1-\delta)k_{jt}}{k_{jt}}\Big)^2 k_{jt}. \tag{14}$$

where c_k determines the slope of the marginal adjustment cost.

B. External Financing

To finance investment projects, each firm uses a combination of internal and external funds, where the sources of external funds are debt and equity. A firm's leverage choice is determined by the standard trade-off: debt financing has a tax advantage over equity financing but carries default risk.

A firm can issue long-term debt of finite maturity. We follow Gomes, Jermann, and Schmid (2016) in modeling the characteristics of the long-term bond and the restructuring procedure in default. Let b_{jt} denote the stock of outstanding liabilities at time t and q_{jt} the per unit market price of these liabilities. The firm is required to pay back a fraction λ of the principal in every period, while the remaining $(1-\lambda)$ remains outstanding, which implies that the debt has an expected life of $\frac{1}{\lambda}$. In addition to principal amortization, the firm is also required to pay a periodic coupon c per unit of outstanding debt in every period.

Hence 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. Upon default, investors take over and restructure the firm. Restructuring entails a deadweight loss that is proportional to capital. After restructuring, investors sell off the equity portion to new owners while continuing to hold the remaining debt. This means that in default states, investors' payoff consists of the firm's after-tax profit $(1-\tau)\big(\exp(z_{t+1}+\eta_{jt+1})k_{jt}^{\alpha} - f\big)$, the total enterprise value $V_{jt+1}(\cdot)$, and the market value of remaining debt $(1-\lambda)q_{jt+1}b_{jt+1}$, net of the deadweight loss ξk_{jt+1}, with $\xi \in (0,1]$.

A firm can also issue equity $e_{jt} < 0$, which entails an issuance cost that captures the underwriting fees. Following Gomes and Schmid (2020), we adopt a reduced-form approach by choosing a proportional equity issuance cost:

$$\Lambda(e_{jt}) = \mathbb{1}_{e_{jt}<0} c_e e_{jt} \tag{15}$$

where $\mathbb{1}_{e_{jt}<0}$ is an indicator variable that equals to 1 if $e_{jt} < 0$ and 0 otherwise.

C. Information Frictions in Debt Markets

While firms have full information, lenders have limited information about firms: they do not observe z_t or η_{jt}. When firms observe the state z_t, lenders observe a signal s_t related to its contemporaneous component ε_t^z instead. As a result, investors never observe the true profit of a firm π_{jt}. They know the law of motion for z_t (11) and that s_t follows the process:

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

where u_t denotes the noise in the signal, and $u_t \sim iid\ N(0,\sigma_{ut}^2)$, $\sigma_{ut}^2 \sim iid\ N(0,\omega_{\sigma_u}^2)$. ε_t^z, η_{jt}, u_t and σ_{ut} are mutually uncorrelated. Lenders' information set at time t includes: (i) the structure of the economy and all of its parameters; (ii) the history of all the model variables through time t, except the current and past realizations of the shocks $\{\varepsilon_t^z,\eta_{jt},\varepsilon_{t-1}^z,\eta_{jt-1},...\}$, which are only observed by the firm; (iii) the history of signals and noise $\Omega_t = \{s_0,s_1,...,s_t,\sigma_{u1},...,\sigma_{ut}\}$.

While lenders observe firms' borrowing and investment decisions $\{b_{jt+1},k_{jt+1}\}$, information on precisely how these decisions depend on z_t is too costly for individual lenders to acquire. Thus, investors cannot infer z_t by inverting firms' policy functions. Instead, investors update the conditional density of the latent variable z_t in each period from Ω_t. Then they use the conditional densities to compute the "lending menu" $q(b_{jt+1},k_{jt+1},\Omega_t)$, consisting of the prices of defaultable bonds for different levels of debt b_{jt+1} and capital k_{jt+1}. We discuss how these prices are determined in Section 4.3.

4.2 Firm's Problem

In each period, a firm defaults on its debt obligation if the equity value $J(\cdot)$ falls below zero. We define the equity value as: $J(k_{jt},b_{jt},z_t,\eta_{jt},\Omega_t) =$

$$\max\left[0, \underbrace{(1-\tau)\big(\exp(z_t+\eta_{jt})k_{jt}^{\alpha}-f\big)}_{\text{after-tax profit}} - \underbrace{\big((1-\tau)c+\lambda\big)b_{jt}}_{\text{debt payment}} + \underbrace{V(k_{jt},b_{jt},z_t,\eta_{jt},\Omega_t)}_{\text{continuation value}}\right] \tag{17}$$

where $V(\cdot)$ summarizes the effect of investment and financing decisions on the equity value:

$$V(k_{jt},b_{jt},z_t,\eta_{jt},\Omega_t) = \max_{b_{jt+1},k_{jt+1},e_{jt}} \Bigg\{ \underbrace{q(b_{jt+1},k_{jt+1},\Omega_t)\Big(b_{jt+1}-(1-\lambda)b_{jt}\Big)}_{\text{value of new debt issues}} \tag{18}$$

$$- \underbrace{\Big(k_{jt+1}-(1-\delta)k_{jt}\Big)+\tau\delta k_{jt}-g(k_{jt},k_{jt+1})}_{\text{investment, tax rebate and adj. cost}} + \underbrace{\Lambda\big(e(k_{jt},b_{jt},z_t,\eta_{jt},k_{jt+1},b_{jt+1},\Omega_t)\big)}_{\text{equity issuance cost}}$$

$$+ \underbrace{\beta \iiiint_{\eta_{jt+1}\geq\eta^*_{jt+1}} J(k_{jt+1},b_{jt+1},z_{t+1},\eta_{jt+1},\Omega_{t+1})\,d\Phi(\eta_{jt+1})\,dF(z_{t+1}|z_t)\,dG(s_{t+1}|\sigma_{ut+1})\,dH(\sigma_{ut+1})}_{\text{expected future equity value}} \Bigg\}.$$

$\eta^*_{jt+1} \equiv \eta^*(k_{jt+1},b_{jt+1},z_{t+1},\Omega_{t+1})$ is the default threshold implicitly defined by:

$$(1-\tau)\big(\exp(z_{t+1}+\eta^*_{jt+1})k^\alpha_{jt+1}-f\big) - \big((1-\tau)c+\lambda\big)b_{jt+1}V(k_{jt+1},b_{jt+1},z_{t+1},\eta^*_{jt+1},\Omega_{t+1}) = 0. \tag{19}$$

Thus, the default decision has a cutoff form: repay in period $t+1$ if $\eta_{jt+1} \geq \eta^*_{jt+1}$, and default otherwise. The definition of equity payout / issuance is given by:

$$e(k_{jt},b_{jt},z_t,\eta_{jt},k_{jt+1},b_{jt+1},\Omega_t) = (1-\tau)\big((z_t+\eta_{jt})k^\alpha_{jt}-f\big) - \big(c+\lambda\big)b_{jt} - \big(k_{jt+1}-(1-\delta)k_{jt}\big)$$
$$- g\big(k_{jt},k_{jt+1}\big) + \tau\big(\delta k_{jt}+cb_{jt}\big) + q(b_{jt+1},k_{jt+1},\Omega_t)\Big(b_{jt+1}-(1-\lambda)b_{jt}\Big). \tag{20}$$

At the beginning of each period, a firm carries debt b_{jt} and capital k_{jt} for the current period's production. Upon observing its profit π_{jt}, and the firm faces the decision of whether or not to repay its debt obligation, $\big(c+\lambda\big)b_{jt}$. If the equity value $J(\cdot)$ is positive, the firm repays, distributes dividends, and decides on its investment and financing decisions for the next period by solving the optimization problem (18). If the firm defaults, the shareholders walk away from the firm, and investors take over and restructure it. After restructuring, investors sell off the equity portion to new owners, who then choose b_{jt+1}, k_{jt+1}, and e_{jt}, and the firm resumes operation.

4.3 Debt Market Equilibrium

Closing the model, the bond market equilibrium must be consistent with the maximization problem posited for the firm (18). Debt investors are risk-neutral and per-

fectly competitive.[8] The market price of debt must satisfy the no-arbitrage condition:

$$q(b_{jt+1},k_{jt+1},\Omega_t) = \beta \times \tag{21}$$

$$\Bigg[\iiint \Big(1-\Phi(\eta^*_{ijt+1})\Big) \underbrace{\Big[c+\lambda+(1-\lambda)q\big(b_{jt+2},k_{jt+2},\Omega_{t+1}\big)\Big]}_{\text{no default payoff}} d\tilde{F}(z_{t+1}|\Omega_t)dG(s_{t+1}|\sigma_{ut+1})dH(\sigma_{ut+1})$$

$$+ \iiiint_{\eta_{t+1}<\eta^*_{ijt+1}} \underbrace{B(b_{jt+1},k_{jt+1},z_{t+1},\eta_{jt+1},\Omega_{t+1})}_{\text{recovery rate in default}} d\Phi(\eta_{jt+1})d\tilde{F}(z_{t+1}|\Omega_t)dG(s_{t+1}|\sigma_{ut+1})dH(\sigma_{ut+1}) \Bigg],$$

where η^*_{t+1} is the default threshold defined by (19), and $\tilde{F}(z_{t+1}|\Omega_t)$ denotes the distribution of z_{t+1} conditional on the history Ω_t. Since investors cannot observe the true state z_t, the price of debt is computed conditional on the signals instead of z_t. Investors continuously update the conditional distribution, as new information arrives in each period. Otherwise the debt pricing function is standard. The first integral contains the payment if there is no default, and the second integral contains the recuperation value following the bankruptcy procedure. The default threshold is defined by (19). The recuperation rate of bond takes the value between 0 and the maximum recovery rate $B_{\max}$:

$$B(b_{jt+1},k_{jt+1},z_{t+1},\eta_{jt+1},\Omega_{t+1}) = \tag{22}$$

$$\min\Bigg[\max\Big[0,\ \Big(\underbrace{(1-\tau)\big(\exp(z_{t+1}+\eta_{jt+1})k^{\alpha}_{jt+1}-f\big)}_{\text{after-tax profit}} + \underbrace{V(k_{jt+1},b_{jt+1},z_{t+1},\eta_{jt+1},\Omega_{t+1})}_{\text{value of firm sold to new owners}}$$

$$+ \underbrace{(1-\lambda)q\big(b_{jt+2},k_{jt+2},\Omega_{t+1}\big)b_{jt+1}}_{\text{value of remaining debt held by lenders}} - \underbrace{\xi k_{jt+1}}_{\text{deadweight loss}} \Big)\frac{1}{b_{jt+1}}\Big],\ B^{\max}\Bigg].$$

Bankruptcy is costly, as a fraction ξ of the firm's capital is lost in liquidation. We measure credit spreads as the yield difference between defaultable and default-free debt with otherwise identical characteristics (e.g. maturity and coupon rate).

5 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. Then we

[8] We assume that investors are risk-neutral in order to focus squarely on our main mechanism, particularly the impact of imperfect information on the levels and dynamics of credit spreads.

examine the model's predictions of bond spreads and investment during the sample period and discuss the effects of information frictions and how they interact with financial frictions in the model.

5.1 Parameterization

The 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). There are 16 parameters in the baseline model:

$$\{\alpha, \delta, \beta, \tau, c, \lambda, B^{\max}, \rho_z, \sigma_\varepsilon, \omega_{\sigma_u}, c_e, c_k, \xi, \mu_\eta, \sigma_\eta, f\}.$$

The first four parameters $\{\alpha, \delta, \beta, \tau\}$ 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). The quarterly depreciation rate δ is 0.025. The rate of time preference $\beta = 0.99$ implies an annualized risk-free rate of 4%. The effective corporate tax rate τ is 30%, in line with the evidence in Graham (2000). The deadweight loss in default ξ is 0.2, similar to the value used in Gomes et al. (2016). 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 five parameters $\{\lambda, B^{\max}, \rho_z, \sigma_\varepsilon, \omega_{\sigma_u}\}$ are calibrated according to their natural data counterpart. We set λ equal to 0.05 per quarter, implying an average expected maturity of five years. This corresponds to the mean maturity of public bonds issued in the U.S. based on the FISD data. We cap the recovery rate of bonds, $B^{\max}$, at 65 percent, which is the top decile of recovery rate conditional on default for corporate bonds during our sample period based on the DRD data. The next two parameters, ρ_z and σ_ε, govern the dynamics of firms' revenues, and we fit an AR(1) to the data on sales-to-asset from the quarterly Compustat database. For the volatility of the noise shock, ω_{σ_u}, we compute the time-series standard deviation of the dispersion of revisions across forecasters from the SPF.

The last six parameters $\{c_e, c_k, \mu_\eta, \sigma_\eta, f, \xi\}$ are jointly calibrated to target moments, where μ_η and σ_η are the mean and standard deviation of the normal distribution $\Phi(\cdot)$. The moments we target are the mean and standard deviation of default rate, the mean profit-to-asset, the mean and standard deviation of leverage, and the mean invest-

Table 5: Parameterization

Parameter	Description	Model
Preferences and technology		
α	Returns to scale	0.65
δ	Depreciation rate	0.025
β	Time preference	0.99
μ_η	Idiosyncratic shock (mean)	0.012
σ_η	Idiosyncratic shock (volatility)	0.023
c_k	Investment adjust. cost	0.12
ρ_z	Profitability shock persistence	0.83
σ_ε	Profitability shock volatility	0.0073
f	fixed cost	0.194
External financing		
τ	Corporate tax rate	0.3
ξ	Bankrupty cost	0.34
c	Coupon rate	0.0101
λ	Debt amortization rate	0.05
c_e	Equity issuance cost	0.182
$B^{\max}$	Maximum recovery rate	0.65
ω_{σ_u}	Volatility of noise shock	0.0062

Note: This table presents the calibrated parameters in the baseline model with imperfect information. The model is calibrated at quarterly frequency. The targeted moments and their data counterparts are reported in Table 6.

ment rate. The mean default rate is chosen to match Moody's value-implied average default rate per quarter, measured by the value of corporate bonds defaulted to the total value of outstanding bonds. The moments on profitability, leverage and investment 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 leverage is determined largely by the cost of equity issuance c_e, and the mean investment rate is affected by the investment adjustment cost c_k. The mean profit-to-asset ratio is largely affected by the mean revenue shock μ_η. The mean default is also affected by the mean revenue shock as well as the bankruptcy cost ξ: holding fixed the mean revenue shock, the larger is the bankruptcy cost, the higher the default rate. The standard deviation of default is determined by the standard deviation of revenue shocks σ_η. The parameters we use are reported in Table 5.

5.2 Algorithm

We solve the model by iterating on both the value function and the debt pricing equation simultaneously. It is worth highlighting the key features that are unique to our imperfect information setting. Specifically, the bond pricing schedule (21) requires computing the conditional density function $\tilde{f}(z_{t+1}|\Omega_t)$ using

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

where $\rho_z z_{t|t}$ and $\Theta_{t+1|t}$ denote the conditional mean and variance, respectively.

With our empirical measure of publicly available signals of profitability – the quarterly information on investor expectations of corporate profits from the Survey of Professional Forecasters (SPF) – we first compute $\left(\rho_z z_{t|t}, \Theta_{t+1|t}\right)$ using a time-varying Kalman filter. 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 $\left(\rho_z z_{t|t}, \Theta_{t+1|t}\right)$, we discretize $(z_{t|t}, \Theta_{t+1|t}, s_t, \sigma_{ut})$ and approximate $\tilde{f}(z_{t+1}|\Omega_t)$ using transition matrix $\widehat{\Pi}_z(z_{t+1}\Big|z_{t|t}, \Theta_{t+1|t})$. With discretized $\left(\rho_z z_{t|t}, \Theta_{t+1|t}\right)$, we can approximate the firm states as $(k_{jt}, b_{jt}, \eta_{jt}, z_t, z_{t|t}, \Theta_{t+1|t})$, and we no longer need to keep track of the entire history Ω_t.

5.3 Model Fit

Table 6 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. Our baseline model with imperfect information is able to capture the countercyclical default rates and credit spreads, and it can generate a reasonable level of spread with a realistic level of default rate and risk-neutral preferences. As explained in Section 3, when investors are uncertain about a low probability event (default), they attach more weight to it. Therefore, in addition to the "default premium," the model-generated spread also features an "uncertainty premium." 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.

We also conduct an event study to compare the model-implied credit spreads to the actual data. In this exercise, instead of simulating the model with randomly drawn shocks and signals, we feed into the model the realized profitability shocks and signals

Table 6: Moment Matching Exercise

Targeted moments	Data	Imperfect information	Full information
Investment rate (mean)	0.018	0.021	0.024
Leverage (mean)	0.267	0.273	0.282
Leverage (std)	0.179	0.164	0.125
Profit to asset (mean)	0.053	0.062	0.071
Default rate	0.013	0.012	0.005
Default rate (std)	0.012	0.009	0.003
Untargeted moments	**Data**	**Imperfect information**	**Full information**
Bond spread (mean)	0.019	0.022	0.007
σ(spread)	0.011	0.015	0.005
Corr(spread, output)	-0.573	-0.438	0.084
Corr(default, output)	-0.431	-0.196	0.067
Corr(leverage,output)	0.126	0.183	0.427
σ(invest)/σ(output)	3.458	2.698	2.162
Corr(invest, output)	0.574	0.890	0.905

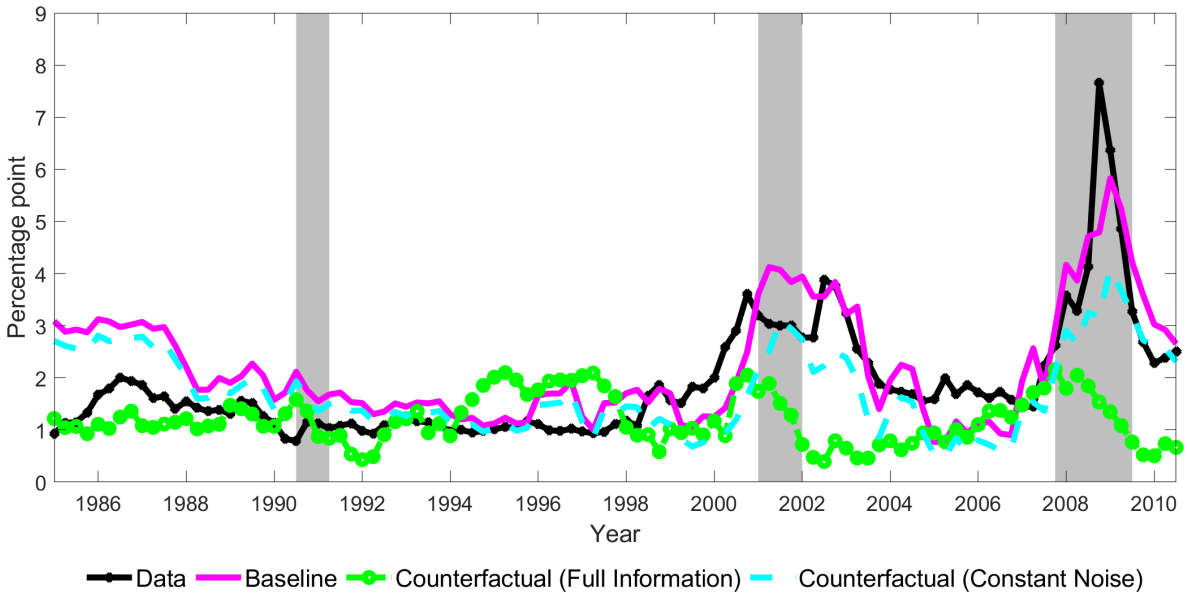
(revisions) from the data, allowing for a time-varying parameter σ_u. Specifically, for each period t in the sample 1985Q1–2010Q4, we first compute the volatility of signals from 1970Q1 to t, yielding a series of $\sigma_{s,t}$. Using $\sigma_{s,t} = \sigma_\varepsilon + \sigma_{u,t}$, we back out $\sigma_{u,t}$ for each t during the sample.[9] Then for each period t in 1985Q1–2010Q4, we run a Kalman filter using the revision series from 1970Q1 to t, given parameter values $\{\rho_z, \sigma_\varepsilon, \sigma_{u,t}\}$. Finally we feed into the model the conditional mean $z_{t|t}$ and variance $\Omega_{t|t}$ period by period. We plot the model-implied credit spread (averaged across firms) from this exercise in Figure 2. The baseline model matches the level of spread reasonably well, and captures the cyclicality variations.

5.4 Effects of Information Frictions

We assess the impact of information frictions through the lens of the model. To this end, we simulate a counterfactual model with the same history of shocks and calibration, but both bond investors and firms have full information. Columns (2) and (3) of Table 6 report the moments generated from the counterfactual model with full in-

[9] Although there is also time variation in the volatility of firm revenue shocks σ_ε, it is significantly less than the time variation in the volatility of signals.

Figure 2: Model-Implied Credit Spreads



Note: This figure shows the time series of corporate bond spread in the US between 1985Q1 and 2010Q4, comparing the data series (black line) and three different model-implied series: the baseline model with imperfect information (purple line), the full information counterfactual (green line), and the constant noise counterfactual (blue line) where σ_{ut} is set to the average in normal times. Shaded areas indicate the NBER recession dates.

formation. We also repeat the event study, in which we feed into the full information model the realized profitability shocks from the data, and compare the model-implied spreads with those from the baseline model (Figure 2).

Effects on credit spreads Table 6 and Figure 2 highlight two main effects of information frictions on credit spreads. First, the level is significantly lower in the full information model, compared to the data and the baseline model. This echoes the "credit spread puzzle" – that the observed spreads on bonds are much larger than what can be explained by empirically plausible default rates. Second, credit spreads are counterfactually procyclical in the full information model. When an adverse profitability shock reduces investment opportunities, the firm deleverages, which in turn lowers its default probability and spread.[10] In other words, in models perturbed by shocks affecting credit demand alone, both spreads and default rates are likely to be procyclical. Although the credit supply "shocks" in our model – i.e. the signals – are correlated with the changes in fundamentals, the two do not coincide, as signals are

[10]Although lower profits imply higher default probabilities and hence potentially higher spreads, this effect is quantitatively dominated by the leverage effect under standard calibrations in this class of models (see, for example, Gomes, Yaron, and Zhang, 2003; Gilchrist, Sim, and Zakrajšek, 2014).

Figure 3: Spread Schedules

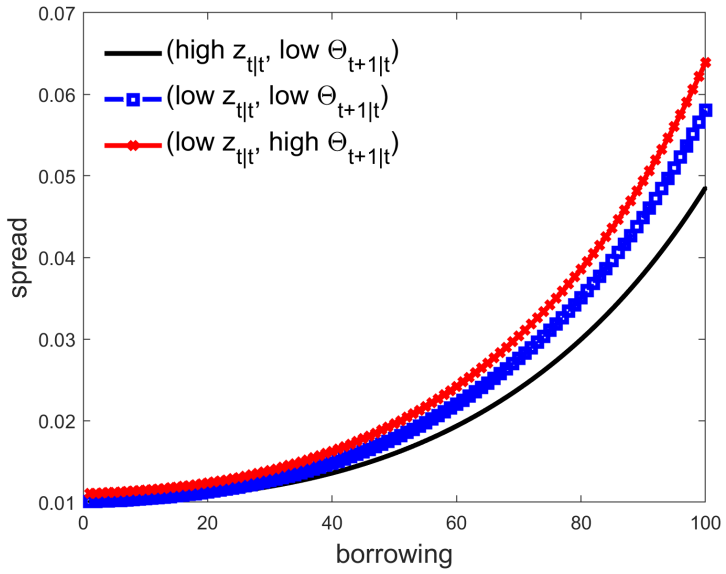
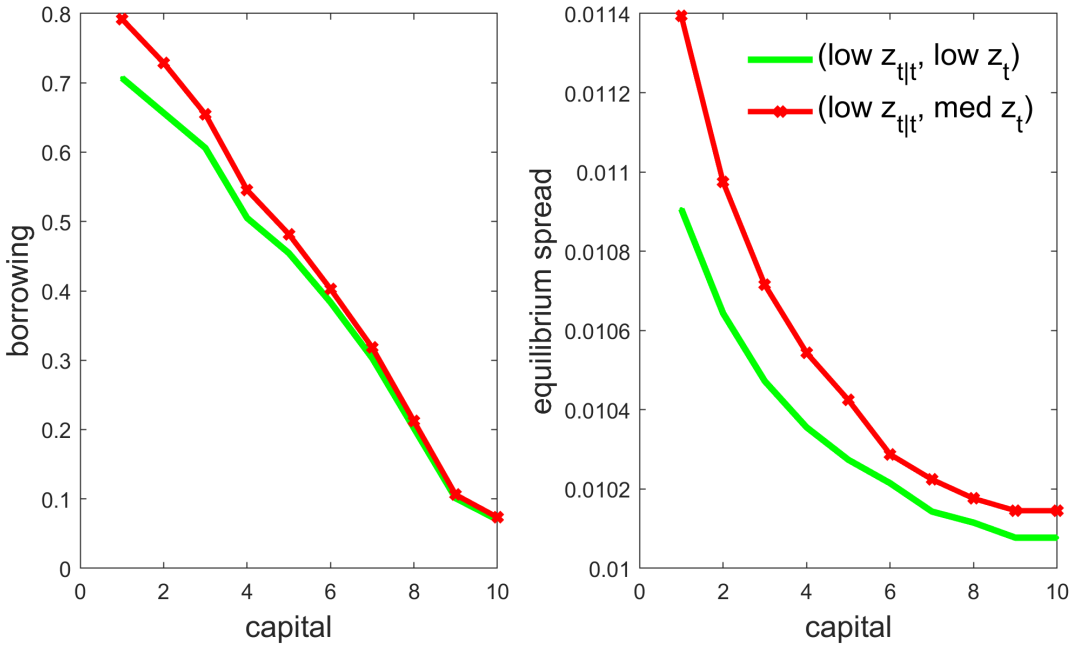


Figure 4: Decision Rules



noisy and exhibit larger swings over the cycle. For instance, during the 2007-09 crisis, investors' estimate of the firm's profitability based on publicly available signals is more pessimistic than the actual profitability. As a result, the effect of the credit supply shift dominates quantitatively.

Effects on investment and firm value Next, we use our model to quantify the loss in investment and equity value $J(\cdot)$ due to information frictions. In Panel C of Table 6, we report the percentage differences between the baseline and full information models for our event study. Information frictions in the debt market have an economically significant real effect: on average, equity value and investment are 2.8% and 11.2% lower, respectively, in the imperfect information model. Moreover, the losses are amplified in the crisis, to 4.7% and 15.6%, respectively. When firms select their leverage and capital stock to optimize their value, they take into account the additional friction, which is investors' uncertainty about the firm's state. As explained above, this translates into an "uncertainty premium", which increases as the signal becomes noisier, and the firms' optimization problem must be consistent with the debt market equilibrium. Therefore, information frictions in the corporate bond market have first-order effects on investment and firm values, especially during the crisis.

6 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 Han-

son (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 Derivations for Results in Section 3

If investors 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:

$$\begin{aligned} q_t &= \beta\Big[1 - \text{Prob}\Big(z_{t+1} < z^* \Big| z_t\Big)\Big] \\ &= \beta\Big[1 - \Phi\Big(\frac{z^* - z_t}{\sigma_\varepsilon}\Big)\Big] \end{aligned} \tag{A.1}$$

If investors only observe a noisy signal s_t about z_t, they compute the conditional distribution of z_{t+1}:

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

and use this to price the bond:

$$\begin{aligned} \tilde{q}_t &= \beta\Big[1 - \text{Prob}\Big(z_{t+1} < z^* \Big| s_t\Big)\Big] \\ &= \beta\left[1 - \Phi\left(\frac{z^* - \bar{z} - \frac{\sigma_z^2}{\sigma_z^2+\sigma_u^2}\left(s_t - \bar{z}\right)}{\sqrt{\sigma_z^2 + \sigma_\varepsilon^2 - \frac{(\sigma_z^2)^2}{\sigma_z^2+\sigma_u^2}}}\right)\right]. \end{aligned} \tag{A.2}$$

1. It is immediate from equation (A.2) 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, $\frac{\partial \tilde{q}_t}{\partial s_t} > 0$.

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

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

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 $\frac{\partial \tilde{q}_t}{\partial \sigma_u^2} < 0$.

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

$$q_t = \beta\Big[1 - \Phi\Big(\frac{z^* - \bar{z}}{\sigma_\varepsilon}\Big)\Big] \tag{A.3}$$

$$\tilde{q}_t = \beta\left[1 - \Phi\left(\frac{z^* - \bar{z}}{\sqrt{\sigma_z^2 + \sigma_\varepsilon^2 - \frac{(\sigma_z^2)^2}{\sigma_z^2+\sigma_u^2}}}\right)\right] \tag{A.4}$$

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

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

Therefore, $\tilde{q}_t$ in (A.4) is smaller than q_t in (A.3), for all $z^* < \bar{z}$.

B Computation

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

We can rewrite the model consisting of equations (11) and (16) in state-space form. The state equation is:

$$\alpha_t = A\alpha_{t-1} + B\eta_t \tag{A.5}$$

where

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

The measurement equation is:

$$s_t = C\alpha_t + u_t \tag{A.6}$$

where $C = \begin{bmatrix} 1 & -\rho_z \end{bmatrix}$ and $\begin{pmatrix} \varepsilon_t^z \\ u_t \end{pmatrix} \sim iidN\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_\varepsilon^2 & 0 \\ 0 & \sigma_u^2 \end{bmatrix}\right)$. If α_1 is normal, then since α_t and s_t are linear combinations of normal errors, then $\left(\alpha_1,...,\alpha_T,\, s_1,...,s_T\right)$ is normally distributed. We introduce the following notation:

$$\begin{aligned} \alpha_t|\mathcal{S}_{t-1} &\sim N\left(\alpha_{t|t-1},\; P_{t|t-1}\right) \\ \alpha_t|\mathcal{S}_t &\sim N\left(\alpha_{t|t},\; P_{t|t}\right) \\ s_t|\mathcal{S}_{t-1} &\sim N\left(s_{t|t-1},\; G_t\right) \end{aligned}$$

In our model, the problem faced by debt investors is to extract the unobserved firm state z_t, and they do so using a Kalman filter. Starting from some initial guess $\alpha_{1|0}$ and $P_{1|0}$, we get $s_{1|0}$ and G_1 (the conditional density of s_1) using:

$$s_{t|t-1} = C\alpha_{t|t-1} \tag{A.7}$$

$$G_t = CP_{t|t-1}C' + \sigma_u^2 \tag{A.8}$$

Then, with the new observation s_1, we can obtain $\alpha_{1|1}$ and $P_{1|1}$ from:

$$\alpha_{t|t} = \alpha_{t|t-1} + P_{t|t-1}C'G_t^{-1}\left(s_t - s_{t|t-1}\right)$$
$$P_{t|t} = P_{t|t-1} - P_{t|t-1}C'G_t^{-1}CP_{t|t-1}$$

From there, we can get $\alpha_{2|1}$ and $P_{2|1}$ using:

$$\alpha_{t|t-1} = A\alpha_{t-1|t-1}$$
$$P_{t|t-1} = AP_{t-1|t-1}A' + BQB'$$

where Q is the covariance matrix of η_t. Then we go back to (A.7) and (A.8) to get $s_{2|1}$ and G_2.

Let $z_t|\mathcal{S}_t \sim N(z_{t|t}, \Omega_{t|t})$ denote the conditional distribution of z_t given $\mathcal{S}_t$. Repeating the procedure above, we find $z_{t|t}$ and $\Omega_{t|t}$ for each quarter using the signal series from 1970Q1 to the current quarter (left panel of Figure 1). We then use these values to jointly solve the firm's problem and the debt market equilibrium.

Table A.1: Summary Statistics of Aggregate Data

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

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

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

Table A.2: Summary Statistics of Micro Data

Panel A: Expectations of Corporate Profits, Firm Level				
	Mean	St.Dev	Min	Max
rev_{it}	-0.64	1.00	-5.36	1.67
Shock to rev_{it}	0.01	1.00	-3.45	3.28
Observations		245,908		
Firms		10,396		
Panel B: Spreads and Other Variables, Firm Level				
	Mean	St.Dev	Min	Max
Spread_{it}	1.69	2.18	-0.54	11.98
Spread_{it} (junk)	23.89	42.63	0.00	1.00
Observations		189,507		
Bonds		4,963		
Firms		775		
Capex growth_{it}	0.03	4.45	-18.10	9.34
Total assets_{it} ($ billion)	3.32	8.56	0.02	58.28
ROA_{it}	2.72	5.52	-18.05	13.54
Observations		245,908		
Firms		10,396		

Note: This table presents the summary for our firm-level variables over our sample period 1982-2010. We measure investor expectations of corporate profits, rev_{it}, as the current revision in investors' expectations of next quarter corporate profits. The measure is constructed as the change between current and last period's investor expectations of next quarter corporate profits. We also consider a residualized version of rev_{it}, Shock to rev_{it}, 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: 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.