The Information Driven Financial Accelerator*

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Abstract

Imperfect information in credit markets is a quantitatively important source of macroeconomic fragility. We calibrate a dynamic model with uninformed debt investors. A deterioration in the profit outlook makes investors pessimistic about firm creditworthiness. In turn, firms perceive that debt is underpriced and cut back investment. We show that: 1) the model matches the size and cyclical variation of credit spreads; 2) imperfect information accounts for about half of the spike in spreads and one-fifth of the contraction in aggregate investment during the US financial crisis; 3) the economic costs of imperfect information for firm value and investment are substantial.

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1 Introduction

Financial crises, their origins and real consequences, have been a central topic in finance and macroeconomics over the last decade. While the 2007 global financial crisis revived interest in understanding the sources of credit market and macroeconomic fragility, the credit market freeze in the recent COVID crisis and the subsequent robust policy response to stabilize credit markets highlight the continued relevance of the topic. A number of stylized facts are now established, including the predictability of corporate bond returns (Greenwood and Hanson, 2013) and, in turn, of business cycle outcomes (Gilchrist and Zakrajšek, 2012; López-Salido, Stein, and Zakrajšek, 2017). Existing theories have focused on frictions in financial intermediation (Gertler and Kiyotaki, 2010; He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014) and behavioral biases including risk neglect and over-reaction (Bordalo, Gennaioli, and Shleifer, 2018). However, despite being recognized as far back as in Keynes (1936), imperfect information has received surprisingly little consideration in the literature. As a result, we still know little about whether imperfect information frictions in credit markets are an important source of macroeconomic fragility and, more broadly, whether they lead to material distortions for firm value and investment.

In an attempt to fill the gap, this paper shows that imperfect information in credit markets is a strong force behind credit cycles. We build a model in which uninformed debt investors update their beliefs about firms' creditworthiness using publicly-available information on quarter-ahead corporate profits from surveys of professional forecasters. We embed this mechanism into an otherwise standard dynamic model of optimal financing and investment to quantify the importance of imperfect information. Using a tightly calibrated version of the model and information from the surveys as one key input, we derive several quantitative results: first, the model can match the size of the credit risk premium, because investors face information uncertainty about firm creditworthiness; second, the model generates counter-cyclical spreads and defaults, because information uncertainty is time-varying; finally and most importantly, imperfect information accounts for a large fraction of the spike in spreads and contraction in aggregate investment during the 2007-09 financial crisis. By contrast, under the same calibration but with perfect information the model can account for only about half of the observed credit risk premiums and for only about a third of the spike in premiums during the crisis, pointing to a large incremental contribution of imperfect information. Overall, our findings indicate that the economic costs of imperfect information frictions in credit markets are large overall and especially so in crisis times.

We start by documenting new stylized facts of the credit cycle. In the time-series, a measure of changes in professional forecasters' expectations of quarter-ahead corporate profits is a strong predictor of excess corporate bond returns 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. Changes 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 premiums in the corporate bond market, which include the excess return on corporate bonds, the excess return on BAA-rated corporate bonds, and the corporate bond premium of Gilchrist and Zakrajšek (2012). On the real side, our survey-based measure has significant forecasting power for various standard economic aggregates, including GDP growth, and business investment and employment growth. As such, our evidence indicates that a deterioration in short-term expectations of corporate profits is at the core of the credit cycle, as it tends to be followed by a subsequent widening of credit spreads, whose timing is, in turn, closely tied to the onset of a contraction in economic activity. This joint predictability of bond returns and macroeconomic aggregates, which we later corroborate with micro data, motivates our quantitative analysis.

Next, we build a tractable quantitative model of firm financing and investment to examine the quantitative importance of imperfect information in credit markets. We introduce learning by uninformed debt-market investors into an otherwise standard dynamic corporate finance setup (Hennessy and Whited, 2007; Kuehn and Schmid, 2014;

Gomes and Schmid, 2020). The model is cast in a standard infinite-horizon, discrete-time stochastic environment with value-maximizing investment and financing decisions under costly external financing. There are two key ingredients: first, credit-market investors are uninformed about firm creditworthiness; second, they form beliefs about it by learning from publicly-available information on quarter-ahead corporate profits from surveys of professional forecasters. 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. In turn, the firm perceives that debt is underpriced and cuts back investment.

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 the sign and magnitude of key stylized facts of the credit cycle more successfully than the perfect information benchmark, especially the fact that credit spreads and defaults are counter-cyclical. By contrast, both credit spreads and default rates are counterfactually pro-cyclical in the perfect information benchmark. The model also boosts the volatility of investment relative to the perfect information benchmark. Finally, in the 2008-2009 crisis, the model generates a persistent widening in credit spreads which is up to three times larger than that predicted by perfect information. The results of a quantitative counterfactual indicate that imperfect information accounts for about half of the spike in spreads and one-fifth of the contraction in aggregate investment during the crisis. 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.

A difficulty in interpreting the motivating evidence is that, while consistent with our model, it may be also consistent with other theories of the credit cycle. For example, while we attempt to control for some omitted variables in additional robustness analysis, there may be other macroeconomic forces, such as deteriorating intermediary balance sheet conditions, that may lead to both worsening profit outlook and higher spreads. To address this issue and further corroborate our mechanism, in the final part of the paper we turn to microdata on firm-level earnings forecasts from 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 a first step toward constructing measures of 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. We show that the predictability evidence is robust to using two approaches to construct these "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).

Our main contribution to the literature on credit cycles is to establish the quantitative importance of imperfect information in credit markets. Closest to our paper is work by Gilchrist and Zakrajšek (2012) and more recently López-Salido, Stein, and Zakrajšek (2017) showing that fluctuations in credit markets are closely tied to future movements in aggregate economic activity. Ben-Rephael, Choi, and Goldstein (2020) show that investors' flows into high-yield bond funds have predictive power for credit spreads and business cycle aggregates, which is consistent with bond fund investors trading profitably on their forecasts of economic trends. The main focus of these papers so far has been empirical, which leaves open the question of sizing up different mechanisms. Our contribution is to highlight imperfect information by credit-market investors, and to take a first step toward quantifying how much it matters for credit cycles. The result has important policy implications, because it suggests that policies that help to anchor investors' expectations about firm creditworthiness, such as direct government subsidies to firms or Fed borrowing facilities, have substantial financial stability benefits.

Our mechanism is distinct but complementary to those that have been previously identified in the literature, 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 results indicate that significant fragility in credit markets and the macroeconomy arises from concerns about the creditworthiness of firms, an issue that has garnered renewed attention in the recent COVID crisis. Relative to the latter, bond prices in our model move in response to the arrival of noisy information, not just to changes in fundamentals. As such, we provide an explanation for the fact that, though tightly linked, credit and real cycles are far from perfectly correlated empirically.[1]

2 Motivating Evidence

We use quarterly information on investor expectations of corporate profits from the Survey of Professional Forecasters (SPF), which is available for a long time series of about 150 quarters between 1970 and 2010. Table 1 presents the summary statistics (annual means) for the two main explanatory variables over our sample period (Panel A) and for the main outcomes (Panel B). The first explanatory variable, Rev_t, is defined as the current revision in investors' expectations of next quarter corporate profits:

$$Rev_t = \mathrm{E}_t\left[\Pi_{t+1}\right] - \mathrm{E}_{t-1}\left[\Pi_{t+1}\right],$$

[1] In terms of other related literatures, a recent literature has started to explore learning in equity markets (see, for example, Adam, Marcet, and Beutel, 2017), but has not yet considered learning in credit markets. We also contribute a quantitative model to the classical literature on learning and herding in finance (Scharfstein and Stein, 1990; Froot, Scharfstein, and Stein, 1992; Bikhchandani, Hirshleifer, and Welch, 1992). Though obtained in a very different context, our result that rational learning can lead to myopia parallels that of Stein (1989). On the empirical side, a large literature following Lakonishok, Shleifer, and Vishny (1992) has shown evidence of correlated trading by institutional investors, which is consistent with herding. Perhaps most relevant to our analysis, recent work by Cai, Han, Li, and Li (2019) shows that herding and correlated trading are especially pronounced among credit market investors and have price impact.

i.e. it is the change between current and last period's investor expectations of next quarter corporate profits. The second explanatory variable of interest, σ_t, measures the dispersion (standard deviation) of revisions across individual forecasters. To ease economic interpretation, both measures are re-scaled by their respective unconditional standard deviation.

Expectations of Corporate Profits and Credit Spreads Table 2 summarizes results on the time-series relation between changes in investor expectations and subsequent risk premiums in the corporate bond market. We report estimates from the following multivariate forecasting regression:

$$R_{t\to t+k} = \alpha + \beta X_t + \gamma Controls_t + u_{t+k}, \tag{1}$$

where $R_{t,t+k}$ is the k-quarter cumulative excess return, with $k = 1,2,4,8$ respectively. X_t is our explanatory variable of interest – that is, either the measure of expectations of corporate profits Rev_t or its dispersion σ_t – in each quarter. Controls include aggregate indicators of 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), the term spread, and lagged excess returns. 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.

We report the main results in Panel A, where we measure expected risk premiums in the corporate bond market using the excess return on corporate bonds. In Panel B, we show robustness to adding controls for other predictors that have been established in the literature, which include growth in aggregate total factor productivity (Bordalo, Gennaioli, and Shleifer, 2018; Bordalo, Gennaioli, Shleifer, and Terry, 2019), the high-yield share of new bond issues (Greenwood and Hanson, 2013), the lagged corporate bond premium (López-Salido, Stein, and Zakrajšek, 2017), and a measure of equity market sentiment from Baker and Wurgler (2006).[2]

Since the measures of expectations are scaled by their respective unconditional standard deviation, we can interpret the coefficients in Table 2 as the change in excess return (in percentage point) associated with a one standard deviation revision in expectations Rev_t, or its noise σ_t. For instance, Panel A of Table 2 reports that a one standard deviation upward revision in investors' expectations lowers the excess return on corporate bonds by about 14 basis points in the following quarter, whereas a one standard deviation increase in the dispersion of revisions raises the spreads by about 24 basis points, which are respectively about 10 percent and 15 percent of the unconditional mean of spreads in our sample (1.6 percentage points).

Expectations of Corporate Profits and the Business Cycle In Table 3, 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. In Appendix Table A.2, we show results for additional aggregate outcomes, which include aggregate consumption and employment growth. We run multivariate time-series forecasting regressions of business cycle aggregates on the component of excess bond returns that is predictable based on investor expectations of corporate profits, controlling for macroeconomic conditions, excess stock returns, short and long rates, and the term spread:

$$BC_{t\to t+k} = \alpha + \beta\widehat{R}_{t\to t+k} + \gamma Controls_t + u_{t+k}, \tag{2}$$

where $BC_{t\to t+k}$ is the business cycle variable k quarters ahead, with $k = 4, 8$ respectively. $\widehat{R}_{t\to t+k}$ is the predicted 4- or 8-quarter cumulative excess return on corporate bonds, estimated from the multivariate forecasting regression of credit spreads using either our

[2]In Panel C we show robustness to orthogonalizing the revisions series with respect to the alternatives rather than adding them as controls. Finally, in Appendix Table A.1 we show additional robustness to using alternatives measures of bond market premiums, the excess return on BAA-rated corporate bonds relative to AAA-rated bonds (Panel B), and the corporate bond premium of Gilchrist and Zakrajšek (2012) (Panel C).

measure of expectations of corporate profits Rev_t or its dispersion σ_t in each quarter. As in the earlier regressions, besides the excess return on corporate bonds (Panel A), we also consider the predicted 4- or 8-quarter cumulative excess return on BAA-rated corporate bonds relative to AAA-rated bonds (Panel B), and the predicted 4- or 8-quarter cumulative excess bond premium by Gilchrist and Zakrajšek (2012).

Importantly, in line with our theory, the mechanism underlying the predictability of real aggregates is the predictability of excess bond return. Consistent with the timing of predictability of debt returns, changes in expectations forecast real economic aggregates over up to 2 years horizons. For instance, Table 3 shows that a one standard deviation upward revision in investors' expectations increases investment by about 10 basis points (-1.46×-0.064) and GDP by about 2 basis points (-0.277×-0.064) in the following year. Moreover, a one standard deviation increase in the dispersion of revisions lowers next year's investment by about 30 basis points and GDP by 12 basis points. The second stage estimates in Table 3 confirm the finding of López-Salido, Stein, and Zakrajšek (2017) that credit spreads are a strong predictor of business cycle variables.

Economic Significance In summary, aggregate evidence indicates that a deterioration in investor expectations of corporate profits tends to be followed by a 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 of the effects of changes in investor expectations, 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 Table 1). Our first stage estimates in Table 2 imply that the combined effect of downward revisions and higher dispersion raised spreads by about 80 basis points ($0.143\times0.44+0.242\times3$), on average, in that period.

Moreover, the combined magnitudes of the first and second stage estimates indicate that the key mechanism at the core of our model is economically meaningful also on the real side. The unconditional mean quarterly growth rates of investment and GDP in our sample are about 1 percentage point and 70 basis points, respectively. For example, the combined estimates in Tables 2 and 3 imply that a one-standard deviation shock to revisions shaves off about 10 percent of the quarterly mean growth rate of investment, which corresponds to about 40 basis points of investment growth on an annual basis. Considering again the 2006 to 2008 period, our estimates imply that the combined effect of downward revisions and higher dispersion lowered investment by almost 1 percentage point ($-1.46\times-0.064\times0.44-0.843\times-0.343\times3$) and GDP by about 40 basis points ($-0.277\times-0.064\times0.44-0.338\times-0.343\times3$), on an average quarterly basis, between 2006 and 2008.

3 Model

Motivated by these observations we next develop a model that we use to examine the quantitative importance of imperfect information in credit markets. This is a dynamic model of optimal financial and investment policy for firms facing financial frictions. A firm can issue equity as well as defaultable debt to finance investment. Debt investors 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 investors' subjective beliefs. In what follows, we show that the interaction of financial and information frictions generates a novel amplification channel. The framework can be extended along several dimensions, one of which is shown in Section 6.

3.1 Economic Environment

A. Technology and Income Processes

Time is discrete and the horizon infinite. A firm produces output y_t using decreasing returns to scale technology, $y_t = z_t k_t^{\alpha}$, with $\alpha < 1$. k_t is the capital input, and z_t is a shock that approximates the following autoregressive processes:

$$\log z_t = \rho_z \log z_{t-1} + \varepsilon_t^z \tag{3}$$

with $\varepsilon_t^z \sim N(0, \sigma_\varepsilon^2)$. After production, the firm receives an idiosyncratic revenue shock η_t that has a normal distribution $\Phi(\eta)$ and are independent over time. Hence the firm's operating profit before tax in each period is:

$$\pi_t = z_t k_t^\alpha - \eta_t.$$

Capital accumulation follows:

$$k_{t+1} = (1-\delta)k_t + i_t,$$

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

$$g(k_t, k_{t+1}) = \frac{c_k}{2}\Big(\frac{k_{t+1} - (1-\delta)k_t}{k_t}\Big)^2 k_t. \tag{4}$$

where c_k determines the slope of the marginal adjustment cost.

B. External Financing

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

The 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_t denote the stock of outstanding liabilities at time t and q_t 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_t, and collect coupon and principal payments, $(c+\lambda)b_{t+1}$, 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 $(1-\tau)(z_{t+1}k_{t+1}^{\alpha}-\eta_{t+1})$, the total enterprise value $V_{t+1}(\cdot)$, and the market value of remaining debt $(1-\lambda)q_{t+1}b_{t+1}$, net of the deadweight loss ξk_{t+1}, with $\xi \in (0,1]$.

The firm can also issue equity $e_t < 0$, 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:

$$\Lambda(e_t) = \mathbb{1}_{e_t<0} c_e e_t \tag{5}$$

where $\mathbb{1}_{e_t<0}$ is an indicator variable that equals to 1 if $e_t < 0$ and 0 otherwise.[3]

C. Information Frictions in Debt Markets

Debt investors know the structure of the economy and all of its parameters. At time t, their information set includes the history of all the model variables through time t, except the current and past realizations of the shocks, which are only observed by the firm. As a result, investors never observe the true profit of a firm.

When the firm observes its state z_t, debt investors observe a signal s_t related to its contemporaneous component ε_t^z instead. They know the law of motion for z_t (3) and that

[3]We also solve a version of the model without equity financing, whereby the firm faces a non-negative dividend constraint in each period, and can only tap into the debt markets to raise external finance. The results are presented in Table A.3 in the appendix.

s_t follows the process:

$$s_t = \varepsilon_t^z + u_t. \tag{6}$$

The noise in the signal, u_t, is i.i.d. normal with zero mean and variance σ_u^2. ε_t^z and u_t are independent. After observing the latest signal s_t, investors update the conditional density of the latent variable z_t using all signals up to the current period, $\mathcal{S}_t = \{s_0, s_1, ..., s_t\}$. Then they use the conditional densities to compute the "lending menu" $q_t(b_{t+1}, k_{t+1}; \mathcal{S}_t)$, consisting of the prices of defaultable bonds for different levels of debt b_{t+1} and capital k_{t+1}. We discuss how these prices are determined in Section 3.3.

3.2 Firm's Problem

Firm managers act in the interest of equity holders. In each period, they can default on their debt obligation if the equity value of the firm $J(\cdot)$ falls below zero. We define the equity value in two parts:

$$J(k_t, b_t, z_t, \eta_t; \mathcal{S}_t) = \max\left[0,\ \underbrace{(1-\tau)\big(z_t k_t^\alpha - \eta_t\big)}_{\text{after-tax profit}} - \underbrace{\big((1-\tau)c + \lambda\big) b_t}_{\text{debt payment}} + \underbrace{V(k_t, b_t, z_t, \eta_t; \mathcal{S}_t)}_{\text{continuation value}}\right], \tag{7}$$

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

$$\begin{aligned} V(k_t, b_t, z_t, \eta_t; \mathcal{S}_t) = \max_{b_{t+1}, k_{t+1}, e_t} \Bigg\{ & \underbrace{q_t(b_{t+1}, k_{t+1}; \mathcal{S}_t)\Big(b_{t+1} - (1-\lambda) b_t\Big)}_{\text{value of new debt issues}} \\ & - \underbrace{\Big(k_{t+1} - (1-\delta)k_t\Big) + \tau\delta k_t - g(k_t, k_{t+1})}_{\text{investment, tax rebate and adj. cost (4)}} + \underbrace{\Lambda\big(e_t(k_t, b_t, z_t, \eta_t, k_{t+1}, b_{t+1})\big)}_{\text{equity issuance cost (5)}} \\ & + \underbrace{\beta \iiint_{\eta_{t+1} \le \eta_{t+1}^*(k_{t+1}, b_{t+1}, z_{t+1}; \mathcal{S}_{t+1})} J\big(k_{t+1}, b_{t+1}, z_{t+1}, \eta_{t+1}; \mathcal{S}_{t+1}\big) d\Phi(\eta_{t+1}) dF(z_{t+1}|z_t) dG(s_{t+1})}_{\text{expected future equity value}} \Bigg\}, \end{aligned} \tag{8}$$

where the current market price of one unit of debt $q_t(b_{t+1}, k_{t+1}; \mathcal{S}_t)$ is determined by a zero profit condition for the lender, which we discuss below. Let $F(z_{t+1}|z_t)$ denote the conditional distributions of z_{t+1}, and $G(s_{t+1})$ the distribution of s_{t+1}. $\eta^*_{t+1}(k_{t+1}, b_{t+1}, z_{t+1}; \mathcal{S}_{t+1})$ is the default threshold implicitly defined by:

$$(1-\tau)\big(z_{t+1}k^{\alpha}_{t+1} - \eta^*_{t+1}\big) - \big((1-\tau)c + \lambda\big)b_{t+1} + V(k_{t+1}, b_{t+1}, z_{t+1}, \eta^*_{t+1}; \mathcal{S}_{t+1}) = 0. \quad (9)$$

Thus, the default decision has a cutoff form: repay in period $t+1$ if $\eta_{t+1} \leq \eta^*_{t+1}$, which occurs with probability $\Phi(\eta^*_{t+1})$, and default otherwise. The definition of equity payout / issuance is given by:

$$\begin{aligned} e_t(k_t, b_t, z_t, \eta_t, k_{t+1}, b_{t+1}) = (1-\tau)\big(z_t k^{\alpha}_t - \eta_t\big) - \big(c+\lambda\big)b_t - \big(k_{t+1} - (1-\delta)k_t\big) - g\big(k_t, k_{t+1}\big) \\ + \tau\big(\delta k_t + c b_t\big) + q_t(b_{t+1}, k_{t+1}; \mathcal{S}_t)\Big(b_{t+1} - (1-\lambda)b_t\Big) \quad (10) \end{aligned}$$

At the beginning of each period, a firm carries debt b_t and capital k_t for the current period's production. Upon observing its profit π_t, and the firm faces the decision of whether or not to repay its debt obligation, $\big(c+\lambda\big)b_t$. 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 (8). 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_{t+1}, k_{t+1}, and e_t, and the firm resumes operation.

3.3 Debt Market Equilibrium

Closing the model, the bond market equilibrium must be consistent with the maximization problem posited for the firm (8). Debt investors are risk-neutral and perfectly competitive.[4] The market price of debt must satisfy the no-arbitrage condition:

$$
\begin{aligned}
&q_t(b_{t+1},k_{t+1};\mathcal{S}_t) = \qquad (11)\\
&\beta\Bigg[\iint \Phi\big(\eta^*_{t+1}(k_{t+1},b_{t+1},z_{t+1};\mathcal{S}_{t+1})\big)\Big[c+\lambda+(1-\lambda)q_{t+1}\big(b_{t+2},k_{t+2};\mathcal{S}_{t+1}\big)\Big]d\tilde{F}(z_{t+1}|\mathcal{S}_t)dG(s_{t+1})\\
&+\iiint_{\eta_{t+1}>\eta^*_{t+1}(k_{t+1},b_{t+1},z_{t+1};\mathcal{S}_{t+1})} B(b_{t+1},k_{t+1},z_{t+1},\eta_{t+1};\mathcal{S}_{t+1})d\Phi(\eta_{t+1})d\tilde{F}(z_{t+1}|\mathcal{S}_t)dG(s_{t+1})\Bigg],
\end{aligned}
$$

where η^*_{t+1} is the default threshold defined by (9). Importantly, since investors cannot observe the firm's true state z_t, the price of debt is computed conditional on the signals instead of z_t. $\tilde{F}(z_{t+1}|\mathcal{S}_t)$ denotes the distribution of z_{t+1} conditional on the history of signals $\mathcal{S}_t$.[5] Investors continuously update the conditional distribution, as new information arrives in each period (see Appendix A for details).

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 (9). The recuperation rate of bond takes the value between 0 and the maximum recovery rate $B_{\max}$:

$$
\begin{aligned}
&B(b_{t+1},k_{t+1},z_{t+1},\eta_{t+1};\mathcal{S}_{t+1}) \qquad (12)\\
&=\min\Bigg[\max\Big[0,\ \Big((1-\tau)\big(z_{t+1}k^{\alpha}_{t+1}-\eta_{t+1}\big)+V(k_{t+1},b_{t+1},z_{t+1},\eta_{t+1};\mathcal{S}_{t+1})\\
&\qquad +(1-\lambda)q_{t+1}\big(b_{t+2},k_{t+2};\mathcal{S}_{t+1}\big)b_{t+1}-\xi k_{t+1}\Big)\frac{1}{b_{t+1}}\Big],\ B^{\max}\Bigg].
\end{aligned}
$$

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).

[4] 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. One robustness exercise we conduct is the general equilibrium extension of the model in Section 6.

[5] To maintain tractability, we do not condition q_t on the inversion of the policy functions b_{t+1} and k_{t+1}, which are nonlinear functions of z_t. Our reasoning is that the information on precisely how the firm's decisions depend on z_t is too costly for individual investors to acquire, and since it gets priced into the market outcome, no investors would have an incentive to acquire it in the first place.

4 Mechanism

Before turning to the numerical analysis, in this section we highlight the mechanisms that are unique to our setting. To focus on how imperfect information about the firm's default probability affects the pricing of bonds, we simplify our model here by assuming 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: the first three concern the impact of information frictions on the level of spreads, and the fourth result speaks to its cyclicality.

4.1 The Level of Credit Spreads

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

$$x_{t+1} = \begin{cases} 1 & \text{if } z_{t+1} \geq z^* \\ 0 & \text{if } z_{t+1} < z^* \end{cases} \tag{13}$$

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:

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

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:

$$\begin{aligned} q_t &= \beta\Big[1 - \text{Prob}\Big(z_{t+1} < z^* \Big| z_t\Big)\Big] \\ &= \beta\Big[1 - \Phi\Big(\frac{z^* - z_t}{\sigma_\varepsilon}\Big)\Big] \end{aligned} \tag{14}$$

where β is the discount factor, and $\Phi(\cdot)$ 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}:

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

and use this to price the bond:

$$\begin{aligned}\tilde{q}_t &= \beta\left[1 - \text{Prob}\left(z_{t+1} < z^* \middle| s_t\right)\right] \\ &= \beta\left[1 - \Phi\left(\frac{z^* - \bar{z} - \frac{\sigma_z^2}{\sigma_z^2+\sigma_u^2}(s_t - \bar{z})}{\sqrt{\sigma_z^2 + \sigma_\varepsilon^2 - \frac{(\sigma_z^2)^2}{\sigma_z^2+\sigma_u^2}}}\right)\right]. \end{aligned} \tag{15}$$

This equation represents the investors' demand for bonds under imperfect information. We highlight four key results by comparing this with the full information benchmark (14). The first observation is immediate:

1. The higher the observed signal s_t, the higher the bond price $\tilde{q}_t$;

The second observation from (15) relates the bond price to the precision of the signal:

2. When the default threshold is sufficiently low, the higher the variance of noise σ_u^2, the lower the bond price $\tilde{q}$.

Appendix B 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 q_t and $\tilde{q}_t$. 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 (14) and (15), we see that:

3. The bond price under imperfect information is lower than the bond price under full information $\tilde{q}_t < q_t$ if the default threshold is relatively low – in this case, $z^* < \bar{z}$.

In other words, for any default threshold $z^* < \bar{z}$, credit spreads are higher under imperfect information.[6] 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. 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. The intuition behind this result 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 2, 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: $\sigma_z^2 + \sigma_\varepsilon^2 - \frac{(\sigma_z^2)^2}{\sigma_z^2 + \sigma_u^2} > \sigma_\varepsilon^2$. Therefore, as shown in the top panel of Figure 2, 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; i.e. investors' subjective belief of the firm's default probability is larger than the actual default probability. In the bottom panel, we show that as s_t increases, the conditional distribution shifts to the right, and the investors' subjective belief of the firm's default probability decreases, for any threshold level z^*.

[6] With one-period debt, credit spreads are defined as $\frac{1}{\tilde{q}_t} - \frac{1}{\beta}$.

4.2 The Cyclicality of Credit Spreads

We illustrate the fourth result intuitively with the help of a graph. Our quantitative model features endogenous default, such that a firm is more likely to default if it is more leveraged, ceteris paribus. For the purpose of illustration, we capture this in a reduced form by assuming that the default threshold is an increasing function of debt, i.e. $z^{*\prime}(b_{t+1}) > 0$. As a result, the bond pricing equation – either equation (14) or (15) – is downward sloping in b_{t+1}. With credit demand denoted by $\bar{b}_0$, the market equilibrium is $(q_0^*, \bar{b}_0)$ in Figure 3.

In technology-driven real business cycle models with costly external finance and endogenous default, 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 3: with fewer investment opportunities, the firm's demand for credit is lower at every q_t. As a result, the bond market equilibrium shifts to $(q_1^*, \bar{b}_1)$. Since the bond pricing function is downward sloping, the new equilibrium features a counterfactually higher bond price (and a lower spread) in an economic downturn.

Panel (b) of Figure 3 shows the bond market equilibrium in a world with information frictions. The difference is that now the bond pricing function is also a function of the noisy signal (see equation (15)). If signals are procyclical, then the bond price schedule shifts downward in a recession: with a lower s_t, $\tilde{q}_t$ is lower at every level of b_{t+1}. This is the forth observation:

4. Learning from procyclical signals can lead to countercyclical credit spreads, especially when the signals are more pessimistic than the fundamentals in a recession.

Therefore, the equilibrium price (spread) and quantity move in the same (opposite) direction in response to the signal, which counteracts the impact of an inward shift in the firm's demand for credit (from $\bar{b}_0$ to $\bar{b}_1$) on q_t. Which force dominates is a quantitative issue, and depends on the relative size of the shifts and how elastic the curves are.

Since the signals are noisy, their movements do not coincide with the movements in fundamentals. In a recession, if the signal is more pessimistic than the decline in fundamental, the supply of credit decreases by more than its demand. This leads to countercyclical spreads, as seen in the 2007-09 financial crisis. As such our mechanism features large shifts in credit supply that originate from information frictions in debt markets.

5 Quantitative Analysis

In this section, we first discuss the calibration of the model, followed by a comparison of moments in the model and the data. Then we 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 Model Calibration

The model is calibrated at quarterly frequency and the sample period is from 1985Q1 to 2010Q4. There are 15 parameters in the baseline model:

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

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 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 $\{\lambda, B^{\max}, \rho_z, \sigma_\varepsilon\}$ are calibrated according to their natural data counterpart. We set λ equal to 0.05 per quarter, implying an average expected maturity of five years. This corresponds to the mean maturity of public bonds issued in the U.S. based on the FISD data. 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 (Moody's Default and Recovery Database). 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.

We use the current revision in professional forecasters' expectations of quarter-ahead corporate profits as our empirical proxy for the signal, which contains new information about firms' fundamentals ε_t^z in each period plus some noise u_t (equation 6). To find the next parameter, the volatility of noise σ_u, we use the model-implied relation:

$$\sigma_s^2 = \sigma_\varepsilon^2 + \sigma_u^2 \tag{16}$$

under the assumption that ε_t^z and u_t are independent. We compute σ_s, the volatility of the revision series, after scaling it by total assets of non-financial corporations, so it is comparable to our estimate for σ_ε.

The last five parameters $\{c_e, c_k, \mu_\eta, \xi, \sigma_\eta\}$ 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 default rate and its standard deviation, the mean profit-to-asset, the mean leverage, and the mean investment 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 4.

We solve the model with value function iterations with the algorithm laid out in Appendix A. Our model solutions have two important features that are unique to our setting. First, the bond pricing schedule is a function of s_t as well as all the past history $\mathcal{S}_{t-1}$. The signals have a direct impact on bond pricing schedule via the conditional density function $\tilde{f}(z_{t+1}|\mathcal{S}_t)$ in equation (11). We compute the conditional mean and variance of z_t using a Kalman filter. Second, we solve the model for different values of the conditional mean and variance as they vary over time, depending on the history. This captures the idea that bond investors revise their pricing schedule in every period, conditional on all past and current information. Therefore, the state variables of a firm are $(k_t, b_t, z_t, \eta_t, s_t, z_{t-1|t-1}, \Omega_{t-1|t-1})$, where $z_{t-1|t-1}$ and $\Omega_{t-1|t-1}$ denote the mean and variance of the conditional distribution $z_{t-1}|\mathcal{S}_{t-1} \sim N(z_{t-1|t-1}, \Omega_{t-1|t-1})$.

5.2 Model Fit

Table 5 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 4, 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 aggregate shocks, we use the realized profitability shocks and signals (revisions) from the data. We filter the signal series with a Kalman filter, and feed into the model the conditional mean $z_{t|t}$ (Figure 6) and variance $\Omega_{t-1|t-1}$ period by period. We plot the model-implied credit spreads (averaged across firms) from this exercise in Figure 7.

As an additional test for model fit, we repeat our empirical exercise in Section 2 using the model-implied spreads from this event study. We use the same measure of expectations Rev_t and the same sample period as in our empirical analysis. Table 6 summarizes the results. Consistent with the data, short-term changes in expectations have significant forecasting power for the model-implied spread. For instance, a one standard deviation increase in revisions lowers the one-quarter ahead model-implied spread by about 28 basis points (Panel A). By influencing external finance premiums, changes in investor expectations of corporate profits also have significant forecasting power for investment and output (Panel B).

5.3 Effects of Information Frictions

We assess the impact of information frictions through the lens of the model. To this end, we simulate another dataset with the same history of shocks and calibration, but where bond investors have the same information set as the firm.[7] Columns (2) and (3) of Table 5 report the moments generated from the counterfactual model with full information. 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 7).

Effects on credit spreads Table 5 and Figure 7 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 puz-

[7]See Appendix C for the setup of the full information model.

zle" – 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. As explained in Section 4.2, when an adverse profitability shock reduces investment opportunities, the firm deleverages, which in turn lowers its default probability and spread.[8] 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 noisy and exhibit larger swings over the cycle. For instance, during the 2007-09 crisis, even with rational learning, investors' estimate of the firm's profitability based on the public information (Figure 6) 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 5, 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.

[8]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).

Economic significance As shown in Figure 4, the revision series was very volatile during the crisis period. To investigate the economic significance of learning from noisy signals, we conduct an additional counterfactual experiment. We continue to assume that there is asymmetric information between debt investors and the firm, and that investors learn from public signals, but for the crisis period, we replace the original signal series with the pre-crisis average. Subsequently, we compute the average spread and annualized change in investment during the crisis, and compare them to their counterparts in the baseline model. As reported in Panel C of Table 5, the average spread is almost halved in this experiment, and the contraction in investment is 20 percent less.

5.4 Interaction of Information and Financial Frictions

Next we study the impact of noisy signals in debt markets on both financial and real variables, and in particular, whether such impact depends on how leveraged the corporate sector is. The latter helps us understand how information and financial frictions interact in the model. To this end, we perform three comparative static exercises by varying the volatility of noise (σ_u) and the equity issuance cost (c_e). Table 7 compares the aggregate moments in our baseline model (low noise-low leverage) and three counterfactual exercises (high noise-low leverage, high noise-high leverage, low noise-high leverage).

Comparing the baseline (column 1) and the first counterfactual model (column 2), we see that, ceteris paribus, having noisier signals leads to higher spread and lower investment on average. We discuss the intuition for the higher spread in Section 4.1. Investment decreases as the firm borrows less when the cost of borrowing is higher. Both variables also become more volatile. The impact on default risk is the result of two forces: the cost of borrowing and the level of indebtedness. Under the baseline calibration, the effect of cost of borrowing dominates, and the average default rate is slightly higher in the counterfactual model.

In the second counterfactual model (column 3), we find that noisier signals lead to a bigger increase in credit spreads when the firm is more leveraged. The default rate is unambiguously higher. Now the firm switches from equity financing to bond financing in the face of higher equity issuance costs. Quantitatively, the increase in debt financing is less than the reduction in equity financing in equilibrium, as the firm endogenizes the increase in borrowing costs. As a result, there is less external financing in total and aggregate investment is lower. Therefore, our model captures an important interaction effect between financial and information frictions: noisier signals have a larger effect on credit spreads and real activity when the corporate sector is more leveraged.

Comparing across the columns in Table 7, we see that higher leverage implies higher credit spreads ($2.8 - 2.1 = 0.7$ percentage points), but the additional impact of having noisier signals is larger ($4.3 - 2.8 = 1.5$ percentage points). Furthermore, the decline in investment due to noisier signals ($1.4 - 2.0 = -0.6$ percentage points) is larger than the decline due to more expensive external financing alone ($2.0 - 2.2 = -0.2$ percentage points). Noisier signals also boost the volatility of investment.

5.5 Extensions to Alternative Learning Rules

The framework we set up in the main text is consistent with rational learning. An additional advantage of our framework is that it can be used to quantify the relative contribution of different mechanisms that drive credit cycles, including behavioral deviations from rationality. In Appendix D, we consider three types of behavioral biases that distort investors expectations of the firm's latent state. First, we consider the case where agents' beliefs are systematically biased toward either the "good" or the "bad" states, depending on whether they are optimistic or pessimistic. Then we consider near-rational learning, in which the investors still update their beliefs about the latent state using the Bayes' rule but they make random mistakes. Lastly, we consider the model implications when investors "overextrapolate", i.e. they believe that the profitability shock ρ_z is more persistent than it actually is. Table A.7 summarizes the model-implied moments under these alternative learning rules.

First, in the models with optimism/pessimism, we calibrate the model to target the historical average default rates for firms issuing high-yield bonds and investment-grade bonds, respectively. We show that the model with pessimistic investors produces higher and more volatile spreads than the model with optimistic investors, which are patterns consistent with the data on high-yield corporate bonds and investment-grade bonds, respectively. In addition, the model generates a comparable (and untargeted) spread between the high-yield and investment-grade, which is 3.4% in the data, and 2.7% in the model. Next, in the model with near-rational learning, the levels of spread and investment are similar to those in the baseline model, but aggregate volatility is unambiguously higher, especially if investors make mistakes more often. Finally, we show that augmenting the rational learning model with overextrapolation improves the model fit on some aggregate moments, such as the correlations of spread and default with output. Overall, these extensions show that while imperfect information represents one potentially important force at play, there are likely other mechanisms that matter. As such, learning does not negate but rather complements existing behavioral explanations.

6 Extended Model in General Equilibrium

In this section, we extend our model to a general equilibrium setting to better understand the aggregate impact of information frictions in the credit market on consumption and employment. The main difference from our baseline model is the introduction of households, which have preferences over consumption and labor. In addition, we show that our main findings in Section 5 are robust in the general equilibrium setting.

6.1 Setup

The economy has a representative household and firm, as well as financial intermediaries that are perfectly competitive. The firm uses capital and labor to produce, subject to the profitability shock z_t. As in our baseline model, the firm can borrow state-uncontingent debt from perfectly competitive financial intermediaries to finance a portion of their input costs, and the firm may default. The household is the owner of the firm and the financial intermediaries. In each period, the household chooses consumption and labor, and collects all incomes in the economy.

The household has time-separable preferences over consumption C_t and labor h_t:

$$U(C_t, h_t) = \mathrm{E}\left\{ \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t^{1-\gamma}}{1-\gamma} - \theta h_t \right] \right\},$$

where $\gamma > 0$ is the coefficient of relative risk aversion. The household faces a per-period budget constraint:

$$C_t \leq w_t h_t + e_t + T_t + \Lambda(e_t),$$

where w_t is real wage, and e_t denotes the dividends from the firm. The corporate income tax and equity issuance cost are rebated to the household in a lump-sum fashion as T_t and $\Lambda(e_t)$, respectively. Hence these costs do not affect the economy-wide resource constraint. The household's intertemporal decisions are determined by the stochastic discount factor (SDF), $M_{t,t+1} = \beta \frac{u_c(C_{t+1}, h_{t+1})}{u_c(C_t, h_t)}$. The labor supply decision is characterized by the static optimization condition $w_t = \frac{-u_h(C_t, h_t)}{u_c(C_t)}$.

The firm's problem is the same as in Section 3 with two exceptions. First, now the firm uses both labor and capital in production, with the following technology:

$$y_t = a_t^{1-(1-\chi)\alpha} \left(k_t^{\chi} h_t^{1-\chi} \right)^{\alpha}$$

where $a_t \equiv e^{z_t}$, χ is the share of capital, $\alpha < 1$ governs the degree of decreasing returns in production as before, and $1 - (1-\chi)\alpha$ is a normalization factor. Hence the firm's intratemporal labor demand satisfies:

$$\Pi_t = \max_{h_t \geq 0} \left\{ a_t^{1-(1-\chi)\alpha} \left(k_t^{\chi} h_t^{1-\chi} \right)^{\alpha} - w_t h_t \right\} = a_t \psi(w_t) k_t^{\kappa}$$

where

$$\kappa = \frac{\chi\alpha}{1-(1-\chi)\alpha} \quad \text{and} \quad \psi(w_t) = [1-(1-\chi)\alpha] \left[\frac{(1-\chi)\alpha}{w_t} \right]^{\frac{(1-\chi)\alpha}{1-(1-\chi)\alpha}},$$

and we can write the firm's before-tax profit as $\pi_t = a_t \psi(w_t) k_t^{\kappa} - \eta_t$, and substitute this in the firm's equity value $J(k_t, b_t, z_t, \eta_t; \mathcal{S}_t)$ (see equation 7). The second difference from our baseline model is that now the firm's future equity value in (8) is discounted by the SDF.

We continue to assume that there is imperfect information in the debt market, such that the firm and its owner (the household) can observe z_t, but financial intermediaries cannot and must learn from a noisy signal s_t. Hence the bond pricing equation (11) continues to hold, except now investors discount their cash flows with the SDF. To close the model, the labor and goods market clearing conditions are given by:

$$h_t^s = h_t^d$$
$$C_t + i_t = y_t - g(k_{t+1}, k_t) - \mathbb{1}_{\eta_t < \eta_t^*(k_t, b_t, z_t; \mathcal{S}_t)} \xi k_t,$$

respectively. In the aggregate resource constraint, $\mathbb{1}_{\eta_t < \eta_t^*(k_t, b_t, z_t; \mathcal{S}_t)} \xi k_t$ denotes the deadweight loss associated with firm default.

6.2 Quantitative Analysis

There are three additional parameters in the extended model, which are χ, γ, and θ. To maintain comparability with our baseline model, we externally calibrate the additional parameters and continue to target the mean default rate, investment rate, profit-to-asset and leverage. We set $\gamma = 1$, so the household's per-period utility is given by $u(C_t, h_t) = \log C_t - \theta h_t$. We set χ, the value-added share of capital in the Cobb-Douglas production function, to 0.36, and normalize θ such that that the real wage in the steady state is one. All the moments and their data counterparts are reported in Table 8. Again we compare the business cycle moments of the two economies, with the only difference being whether financial intermediaries can observe the firms' latent state z_t.[9]

There are three main observations from Table 8. First, the benchmark economy exhibits the hallmark features of an RBC model, with the investment about three times more

[9]We simulate the general equilibrium model for 10,000 periods (after dropping the first 200) by feeding into the model randomly drawn shocks ε_t and η_t, as well as signals s_t. For tractability, the general equilibrium model features a representative firm, and we compute the default rate as the number of times the firm defaults over the total number of periods. This differs from our baseline model in Section 3, which features heterogeneous firms receiving idiosyncratic revenue shocks, and the default rate is the fraction of defaulting firms. Recall that default is followed by restructuring (subject to a deadweight loss) and not firm exit in the model. This assumption enhances tractability, since entry and exit are not crucial for our mechanism.

volatile than output and highly correlated with output, consumption, and hours worked. Second, one of our main findings from the baseline model is robust in the GE extension: spreads and defaults are both counter-cyclical. Third, comparing the two economies in Table 8, the full information model exhibits lower volatilities for consumption, employment and investment. This is because the asymmetric information problem in the bond market affects the aggregate variables through firm's hiring and investment decisions as well as households' budget constraint.

We assess quantitatively the impact of information frictions by conducting the event study described in Section 5: we feed into each model the realized profitability shocks and signals from the data, and compare the percentage differences in investment and equity value between the baseline and full information models. We find that the losses in investment and equity value due to imperfect information are 3.7% and 0.82%, respectively. These numbers are smaller than the losses in the partial equilibrium model, as general equilibrium forces dampen the impact of frictions. We also find that the utility gain associated with eliminating asymmetric information in corporate bond markets amounts to 0.36% of consumption per period. The welfare gains arise mainly through higher dividend payments and fewer defaults on bonds.

7 Evidence from Microdata

Section 2 presents motivational evidence from aggregate data, but some caution is needed in drawing firm conclusions. 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.

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.

7.1 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 I/B/E/S Detail History File (unadjusted) for analyst-by-analyst EPS forecasts, ICE/IDC and the Warga database for bond-level spreads, and quarterly Compustat for firm balance sheet information. We avoid using the off-the-shelf consensus forecast from the I/B/E/S 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).

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:

$$Rev_{it} = \mathrm{E}_t\left[\Pi_{i,t+1}\right] - \mathrm{E}_{t-1}\left[\Pi_{i,t+1}\right],$$

i.e. the firm-level measure is defined as the change between current and last period's forecasts of next quarter corporate profits.[10] 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}.

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. As the I/B/E/S information is available starting from 1982, the resulting samples are panels of about 5,000 bonds (800 firms) and 10,000 firms between 1982 and 2010,

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

respectively. Table 1 presents the summary statistics for the main explanatory variables over the sample period (Panel C) and for the main outcomes (Panel D).

7.2 Cross-Sectional Correlations

We start by using panel regressions to confirm that the negative (positive) time-series relation between changes in expectations of corporate profits and corporate credit spreads (investment) in the aggregate also holds in the cross-section of firms. To that end, we regress spreads and investment on our firm-level measure of revisions, while controlling for standard co-variates (size and current profitability (ROA)). We consider two baseline specifications, with the dependent variable 4- and 8-quarter ahead, and for two periods, the full sample and the "crisis" period (2005-2010). The baseline estimates are reported in Panels A and B of Table 9, respectively (Columns (1)-(4)). The coefficient on revisions is robustly negative (positive) and significant for spreads (investment) across the two samples and for both the 4- and 8-quarter ahead specifications. For the baseline specification in Column (1), one standard deviation downward change in revisions is associated with about 20 basis points increase in spreads 4-quarters ahead, which is equal to about 10% of the sample mean value of spreads. For investment, the effect is also economically significant at about 30 basis points, which is also equal to about 10% of the sample mean. Estimates in the crisis are a bit larger than those for the entire sample.

7.3 Evidence from "Shocks" to Revisions

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 use two empirical strategies. First, we isolate changes or "shocks" to revisions, denoted by ε_{it}^{Rev}, that are unrelated to realized macroeconomic and firm fundamentals. Second, we exploit "shocks" to revisions around brokerage house mergers.

Similar to Fracassi, Petry, and Tate (2016), we construct a measure of "shocks" to revisions based on analyst-specific change in expectations that are plausibly independent from realized changes in firm fundamentals. 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. Specifically, the regression specification is given by:

$$Rev_{jit} = \alpha_{it} + \beta_{jt} Analyst_{jit} + \varepsilon_{jit}, \tag{17}$$

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. $Analyst_{jit}$ 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.

This approach makes it unnecessary to include any time-varying controls for firm fundamentals such as size and profitability, since they cannot be identified independently from the fixed effects. It also mitigates selection concerns. The matching of analysts to firms is unlikely to be random; for example, analyst teams are often organized by sector. However, 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. We calculate the average of the resulting analyst-specific shocks within a given firm-quarter to construct the firm-level shock, ε_{it}^{Rev}, i.e.

$$\varepsilon_{it}^{Rev} = \frac{1}{N_{it}} \sum_{j} \hat{\beta}_{jt} Analyst_{jit} \tag{18}$$

where N_{it} denotes the number of analysts for a given firm i and quarter t.

We regress the k-quarter cumulative excess return and firm investment, in turn, on "shocks" to expectations, controlling for firm size and current profitability, and time fixed effects τ_t:

$$Y_{it \to it+k} = \alpha + \beta \varepsilon_{it}^{Rev} + \gamma Controls_{it} + \tau_t + u_{it+k}, \tag{19}$$

with $k = 4, 8$ respectively, and the dependent variable, Y, equal to excess return and firm investment. As shown in Columns (5)-(8) of Table 9, the negative (positive) relation between changes in expectations of corporate profits and corporate credit spreads (investment) continues to be significant, especially during the crisis period.

Second, we exploit 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 is that, as documented by Hong and Kacperczyk (2010), 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. 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).

Using brokerage house merges as an instrument for Rev_{it}, we estimate the following with two-stage least square estimation:

$$R_{it \to it+k} = \alpha + \beta Rev_{it} + \gamma Controls_{it} + \tau_t + u_{it+k}, \tag{20}$$

with $k = 4, 8$ respectively. As above, firm-level controls include firm size and current profitability, and τ_t denotes time fixed effects. To assess the impact on firm investment, we regress investment on the predictable component of excess bond returns from (20), $R_{it \to it+k}$. The results are reported in Columns (9)-(10) of Table 9.

The estimates for spreads and investment remain large and strongly statistically significant 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, Bordalo, Gennaioli, Shleifer, and Terry, 2019). 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 diagnostic expectations are distinct and complementary mechanisms.

7.4 Additional Supporting Evidence

Lastly, we use sample-split analysis to offer additional supporting evidence (see Table A.8 in the appendix). We regress changes in spreads and investment on a "Crisis$_t$" indicator that is equal to one between 2007Q4 and 2009Q2:

$$\Delta R_{it} = \alpha + \beta Crisis_t + \gamma Controls_{it} + u_{it}. \tag{21}$$

The resulting estimate of β measures the average size of the change in spreads and investment in the crisis. We split the sample based on proxies for the type of information frictions that are emphasized by our model. First, we consider whether firms had negative earnings revisions, which we proxy by splitting the sample based on whether firms are above or below the median of Rev_{it}. In line with the unique prediction of our model, firms with the most negative revisions experienced an about 50% bigger spike in spreads and twice as large a contraction in investment (Columns (1)-(2)).

Second, we further stratify the sample based on whether firms with the most negative revisions also had their debt rated as junk (triple B or lower, Column (3)). Third and final, we consider a sub-sample of firms where analysts are most reliant on public signal (Column (4)). Based on our model, these firms should be most sensitive to macro conditions. To measure reliance on public signal, we follow Chen and Jiang (2006) and use analyst-level regressions to calculate for each analyst the correlation between forecast errors[11] and deviations from consensus forecast (see their equation 7). Because a negative (positive) correlation is indicative of over-weighting of the public (private) signal, we classify as *Most Reliant on Public Signal* those firms whose analysts have a correlation below the mean. Consistent with the cost of debt financing for junk-rated firms being the most information sensitive, the spike in spreads was outsized for these firms. As it was for firms whose analysts were most reliant on the public signal, which also experienced a large contraction in investment.

8 Conclusion

In order to better understand the consequences of information imperfections in debt markets, we have combined macro and micro data on professional forecasts of corporate profits, bond returns, and corporate investment with a novel 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, and perhaps more important as a contribution, we have developed a quantitative model that incorporates this mechanism and 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 pre-

[11] We are aware of the issue that arises when calculating forecast errors by matching actual reported EPS from the I/B/E/S unadjusted actuals file with consensus forecasts, which is due to stock splits occurring between the EPS forecast and the actual earnings announcement. We address the issue by calculating the forecast errors based on actual and forecasted EPS that are adjusted using the CRSP cumulative adjustment factors, which resolves the issue by ensuring that both actual EPS and EPS forecasts are expressed on the same share basis.

dictability 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 debt markets, which had not yet been the subject of formal analysis and testing despite the fact that learning is a central idea in modern financial economics.

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Table 1: Summary Statistics:
Measuring Investor Expectations of Corporate Profits

Panels A and B of this table present summary statistics for our aggregate variables, the two main explanatory variables over our sample period from 1971-2010 (Panel A) and the main outcomes (Panel B). We measure investor expectations of corporate profits, Rev_t, as the current revision in investors' expectations of next quarter corporate profits. The measure is contructed 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, 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.

Panel A: Expectations of Corporate Profits, Aggregate Level					
Year	Rev_t	σ_t	Year	Rev_t	σ_t
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
			Obs.	151	151

Panel B: Aggregate Spreads and Macro Variables (1971-2010)				
	Mean	St.Dev	Min	Max
Bond Spread$_t$	1.59	1.03	0.56	7.66
BAA-AAA Spread$_t$	1.11	0.47	0.56	3.02
Excess Bond Premium$_t$	0.03	0.47	-0.89	2.05
GDP Growth$_t$	0.70	0.85	-2.05	3.93
Bus. Investment Gr$_t$.	1.08	2.49	-10.28	8.43
Employment Growth$_t$	0.39	0.68	-2.21	1.99
Consumption Growth$_t$	0.77	0.69	-2.27	2.34

Table 1: Summary Statistics:
Measuring Investor Expectations of Corporate Profits (Continued)

Panels C and D of this table present summary statistics for our firm-level variables, the main explanatory variables over our sample period from 1982-2010 (Panel C) and the main outcomes (Panel D). We measure investor expectations of corporate profits, Rev_{it}, as the current revision in investors' expectations of next quarter corporate profits. The measure is contructed as the change between current and last period's investor expectations of next quarter corporate profits. 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. 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_t. *Reliance on Public Signal*$_{it}$ is based on Chen and Jiang (2006) and is defined as the correlation between forecast errors and deviations from consensus forecast, with a negative correlation indicating over-weighting of the public signal. 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.

Panel C: Expectations of Corporate Profits, Firm Level (1982-2010)				
	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
Reliance on Public Signal$_{it}$	-0.32	1.00	-3.69	2.48
Obs=245,908				
Firms=10,396				

Panel B: Spreads and Micro Variables, Firm Level (1982-2010)				
	Mean	St.Dev	Min	Max
Bond Spread$_{it}$	1.69	2.18	-0.54	11.98
Rated Junk$_{it}$	23.89	42.63	0.00	1.00
Obs=189,507				
Bonds=4,963				
Firms=775				
Capex Gr$_{it}$.	0.03	4.45	-18.10	9.34
Total Assets$_{it}$($B)	3.32	8.56	0.02	58.28
ROA$_{it}$	2.72	5.52	-18.05	13.54
Obs=245,908				
Firms=10,396				

Table 2: Aggregate Evidence: Multivariate Forecasting Regressions of Credit Spreads

This table summarizes results of multivariate time-series forecasting regressions of excess bond returns on investor expectations of corporate profits, controlling for 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), the term spread, and lagged excess returns:

$$R_{t \to t+k} = \alpha + \beta X_t + \gamma Controls_t + u_{t+k}$$

X_t is our measure of expectations of corporate profits and its noise, in turn, in each quarter. 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, 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 is from the Survey of Professional Forecasters. In Panel A, the dependent variable is the 1-, 2-, 3-, 4- or 8-quarter cumulative excess return on corporate bonds. In Panels B-C, we show robustness to alternative mechanism. The dependent variable is the 4- or 8-quarter cumulative excess return on corporate bonds, the explanatory variable is Rev_t, and we add controls for alternative explanations (Panel B) or orthogonalize Rev_t with respect to the alternatives (Panel C). t-statistics for k-period forecasting regressions are based on Newey-West (1987) standard errors allowing for serial correlation up to k-1 lags.

Panel A: Excess Return on Corporate Bonds

	Rev_t					σ_t				
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
β	-0.143	-0.105	-0.100	-0.064	-0.060	0.242	0.261	0.291	0.343	0.520
[t]	[-2.78]	[-2.28]	[-3.00]	[-2.08]	[-2.41]	[3.18]	[3.23]	[3.26]	[3.06]	[4.67]
R^2	0.77	0.81	0.83	0.84	0.87	0.78	0.76	0.72	0.69	0.66

Panel B: Robustness to Controlling for Other Mechanisms

	Other Macro-Fin		HY Share		Lagged EBP		Equity Sentiment	
	4-qtr	8-qtr	4-qtr	8-qtr	4-qtr	8-qtr	4-qtr	8-qtr
β	-0.180	-0.116	-0.223	-0.163	-0.235	-0.177	-0.197	-0.121
[t]	[-2.01]	[-1.70]	[-2.81]	[-3.20]	[-2.72]	[-3.17]	[-2.10]	[-1.68]
TFP	-0.079	-0.056						
[t]	[-2.31]	[-1.70]						
HY Share			-0.026	-0.023				
[t]			[-2.37]	[-2.41]				
Lag EBP					-0.936	-1.212		
[t]					[-2.37]	[-2.59]		
Equity S.							0.192	0.178
[t]							[1.65]	[1.39]
R^2	0.40	0.33	0.43	0.45	0.44	0.51	0.37	0.32

Panel C: Robustness to Orthogonalizing Rev_t by

	Other Macro-Fin		HY Share		Lagged EBP		Equity Sentiment	
	4-qtr	8-qtr	4-qtr	8-qtr	4-qtr	8-qtr	4-qtr	8-qtr
β	-0.053	-0.047	-0.054	-0.043	-0.050	-0.045	-0.067	-0.060
[t]	[-1.84]	[-1.80]	[-1.74]	[-1.73]	[-1.72]	[-1.91]	[-2.18]	[-2.43]
R^2	0.84	0.87	0.85	0.87	0.84	0.87	0.84	0.87

Table 3: Aggregate Evidence:
Expectations of Corporate Profits, Credit Spreads, and the Business Cycle

This table summarizes results of multivariate time-series forecasting regressions of business cycle aggregates on the component of excess bond returns that is predictable based on investor expectations of corporate profits, controlling for 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), the term spread:

$$BC_{t\to t+k} = \alpha + \beta\widehat{R}_{t\to t+k} + \gamma Controls_t + u_{t+k}$$

$\widehat{R}_{t\to t+k}$is estimated from the multivariate forecasting regression of credit spreads, $R_{t\to t+k} = \alpha + \beta X_t + \gamma Controls_t + u_{t+k}$,where $X_t$is our measure of expectations of corporate profits and its noise, in turn, in each quarter. We measure investor expectations of corporate profits, Rev_t, as the current revision in investors' expectations of next quarter corporate profits. The measure is contructed 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, 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 is from the Survey of Professional Forecasters. In Panel A, $\widehat{R}_{t\to t+k}$is the predicted 4- or 8-quarter cumulative excess return on corporate bonds. In Panels B and C, we examine robustness to using two alternative measures of excess returns, the predicted 4- or 8-quarter cumulative excess return on BBB-minus rated corporate bonds relative to AAA-rated bonds (Panel B) and the predicted 4- or 8-quarter cumulative excess bond premium by Gilchrist and Zakrajšek (2012). Robust t-statistics are shown in brackets.

Panel A: Excess Return on Corporate Bonds								
	Rev_t				σ_t			
	Inv 4-qtr	Inv 8-qtr	GDP 4-qtr	GDP 8-qtr	Inv 4-qtr	Inv 8-qtr	GDP 4-qtr	GDP 8-qtr
β	-1.460	-1.319	-0.277	-0.209	-0.843	-0.969	-0.338	-0.259
[t]	[-1.72]	[-3.68]	[-2.16]	[-1.40]	[-2.67]	[-5.74]	[-3.97]	[-5.05]
R^2	0.66	0.72	0.56	0.55	0.63	0.70	0.56	0.57
Panel B: Excess Return on BAA-Rated Corporate Bonds								
	Rev_t				σ_t			
	Inv 4-qtr	Inv 8-qtr	GDP 4-qtr	GDP 8-qtr	Inv 4-qtr	Inv 8-qtr	GDP 4-qtr	GDP 8-qtr
β	-4.753	-3.978	-0.579	-0.467	-1.873	-2.429	-0.751	-0.648
[t]	[-1.26]	[-1.70]	[-2.07]	[-1.40]	[-2.47]	[-4.78]	[-3.54]	[-4.60]
R^2	0.33	0.36	0.52	0.52	0.51	0.48	0.43	0.49
Panel C: Excess Corporate Bond Premium								
	Rev_t				σ_t			
	Inv 4-qtr	Inv 8-qtr	GDP 4-qtr	GDP 8-qtr	Inv 4-qtr	Inv 8-qtr	GDP 4-qtr	GDP 8-qtr
β	-2.906	-2.527	-0.544	-0.414	-5.407	-4.530	-2.168	-1.209
[t]	[-1.75]	[-2.94]	[-1.92]	[-1.16]	[-2.89]	[-5.32]	[-2.15]	[-3.89]
R^2	0.66	0.70	0.53	0.52	0.49	0.62	0.32	0.33

Table 4: Baseline 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)	0.178
σ_η	Idiosyncratic shock (volatility)	0.145
c_k	Investment adjust. cost	0.12
ρ_z	Profitability shock persistence	0.83
σ_ε	Profitability shock volatility	0.0073
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
Learning		
σ_s	Volatility of signal	0.0091
σ_u	Volatility of noise	0.0054

Note: This table presents the calibrated parameters in the baseline model with imperfect information. The model is calibrated at quarterly frequency. These choices are discussed in detail in Section 5. The targeted moments and their data counterparts are reported in Table 5.

Table 5: Model Fit

Panel A: Targeted moments	**Data**	**Baseline**	**Full information**
	(1)	(2)	(3)
Investment rate (mean)	0.018	0.022	0.026
Leverage (mean)	0.267	0.291	0.302
Profit to asset (mean)	0.053	0.068	0.081
Default rate	0.013	0.016	0.011
σ(default)	0.012	0.013	0.008
Panel B: Untargeted moments	**Data**	**Baseline**	**Full information**
	(1)	(2)	(3)
Bond spread (mean)	0.019	0.021	0.010
σ(spread)	0.011	0.018	0.008
Corr(spread, output)	−0.573	−0.259	0.212
Corr(default, output)	−0.431	−0.163	0.176
σ(invest)/σ(output)	3.458	2.394	2.162
Corr(invest, output)	0.574	0.890	0.905
Panel C: Impact of Imperfect Information			
On investment		−11.2%	
On investment, crisis		−15.6%	
On equity value		−2.8%	
On equity value, crisis		−4.7%	
Panel D: Economic Significance of Noisy Signals			
Average spread, crisis		0.048	
Counterfactual average spread, crisis		0.025	
Annualized change in investment, crisis		−0.126	
Counterfactual change in investment, crisis		−0.102 (−19.0%)	

Note: Panel A reports the targeted moments, and Panel B reports the untargeted fit of the model. The data moments are calculated from Compustat. The model-implied moments are based on 2,000 quarters of simulated data for 5,000 firms, where the aggregate and idiosyncratic shocks are randomly drawn. Columns (2) and (3) compare the moments generated in the models with (baseline, column 2) and without information frictions (counterfactual, column 3) information frictions. The main difference between the two models lies in the bond pricing equation. In the baseline model, the price of debt is a function of the history of all publicly available signals up to the current period $\mathcal{S}_t = \{s_0, s_1, ..., s_t\}$ (equation 11). In the counterfactual model, investors can observe the firm's state z_t so the price of debt is a function of z_t (equation A.7). Panel C reports the percentage differences in investment and equity value between the baseline model and the full information model for an event study. In this study, we feed into each model the realized profitability shocks and signals (revisions) from the data. In Panel D, we report the average spread and annualized change in investment, respectively, during the 2007-09 crisis in our event study. We compare the results from the baseline model with those from a different counterfactual model. In this counterfactual, investors still have imperfect information and learn rationally as in the baseline, but we replace the signals (revisions) during crisis with the pre-crisis average.

Table 6: Model-Implied Forecasting Regressions

Panel A: Expected Corporate Profits and Credit Spreads

$$R_{t\to t+k} = \alpha + \beta Rev_t + u_{t+k}$$

	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
β	-0.283	-0.275	-0.231	-0.203	-0.110
[t]	[-3.29]	[-3.16]	[-2.47]	[-2.08]	[-1.71]
R^2	0.156	0.149	0.110	0.089	0.030

Panel B: Expected Corporate Profits and Investment

$$BC_{t\to t+k} = \alpha + \beta \widehat{R}_{t\to t+k} + u_{t+k}$$

	Inv 4-qtr	Inv 8-qtr		Output 4-qtr	Output 8-qtr
β	-0.715	-0.388		-0.106	-0.065
[t]	[-2.52]	[-2.13]		[-2.44]	[-2.08]
R^2	0.063	0.017		0.061	0.014

Note: This table presents the results of model-implied forecasting regressions for our event study. In this study, we feed into our model the realized profitability shocks and signals (revisions) from the data. In Panel A, we regress the model-implied spread on investor expectations of corporate profits. The dependent variable $R_{t\to t+k}$ is the 1-,2-,3-,4-, or 8-quarter cumulative excess return on corporate bonds, respectively. The independent variable Rev_t is the current revision in investors' expectations of next quarter corporate profits, scaled by its standard deviation. In Panel B, we regress business cycle aggregates on the component of the model-implied spread that is predictable based on investor expectations of corporate profits. The dependent variable $BC_{t\to t+k}$ is the 4-, or 8-quarter ahead investment and output, respectively. The independent variable $\hat{R}_{t\to t+k}$ is the predicted 4- or 8-quarter cumulative excess return on corporate bonds, estimated from the forecasting regression in Panel A.

Table 7: Interaction Effects of Noisy Signals and Leverage

	Baseline		**Comparative Statics**	
	(1)	(2)	(3)	(4)
	$[\sigma_u, c_e]$	$[2\sigma_u, c_e]$	$[2\sigma_u, 2c_e]$	$[\sigma_u, 2c_e]$
First moments				
Default rate	0.016	0.023	0.035	0.025
Bond spread	0.021	0.031	0.043	0.028
Leverage	0.291	0.262	0.308	0.338
Investment	0.022	0.017	0.014	0.020
Second moments				
Corr(default, output)	−0.163	−0.144	−0.176	−0.192
Corr(spread, output)	−0.259	−0.215	−0.229	−0.286
Corr(invest, output)	0.890	0.877	0.872	0.885
RSD(default)	0.813	0.905	0.932	0.795
RSD(spread)	0.857	0.936	0.912	0.832
σ(invest)/σ(output)	2.394	2.502	2.586	2.470

Note: This table reports the aggregate moments for different values of σ_u (the volatility of noise) and c_e (the cost of equity financing). Column (1) presents the moments under the baseline calibration, as reported in Table 4. We consider three comparative statics: (i) doubling σ_u (column (2)); (ii) doubling σ_u and c_e (column (3)); (iii) doubling c_e (column (4)). RSD is the relative standard deviation (i.e. standard deviation divided by the mean).

Table 8: Model Fit: GE Extension

Panel A: Targeted moments	**Data**	**Baseline**	**Full information**
	(1)	(2)	(3)
Investment rate (mean)	0.018	0.024	0.025
Leverage (mean)	0.267	0.305	0.312
Profit to asset (mean)	0.053	0.049	0.057
Default rate	0.013	0.016	0.014

Panel B: Untargeted moments	**Data**	**Baseline**	**Full information**
	(1)	(2)	(3)
Spread			
Bond spread (mean)	0.019	0.022	0.015
σ(spread)	0.011	0.020	0.012
Corr(spread, output)	−0.573	−0.262	0.171
Default risk			
Corr(default, output)	−0.431	−0.318	0.125
Investment			
σ(invest)/σ(output)	3.458	2.517	2.323
Corr(investment, output)	0.574	0.903	0.911
Consumption			
σ(consume)/σ(output)	0.420	0.958	0.945
Corr(consumption, output)	0.557	0.983	0.989
Employment			
σ(employ)/σ(output)	0.603	0.496	0.471
Corr(employment, output)	0.651	0.746	0.782

Panel C: Impact of Imperfect Information			
On investment		−3.7%	
On equity value		−0.82%	

Note: Panel A reports the targeted moments in the GE model; panel B reports the untargeted fit of the model. The data moments are calculated from Compustat. The model-implied moments are based on 10,000 quarters of simulated data, with randomly drawn shocks. Columns (2) and (3) compare the model-generated moments in the model with and without information frictions. In the baseline model, the price of debt is a function of the history of all publicly available signals up to the current period $\mathcal{S}_t = \{s_0, s_1, ..., s_t\}$ (equation 11). In the counterfactual model, investors can observe the firm's state z_t so the price of debt is a function of z_t (equation A.7). Panel C reports the percentage differences in investment and equity value between the baseline model and the full information model for an event study, where we feed into each model the realized profitability shocks and signals (revisions) from the data.

Table 9: Evidence from Microdata:
Expectations of Corporate Profits, Credit Spreads, and Investment

This table summarizes results of firm-level forecasting regressions of excess bond returns (Panel A) and investment (Panel B) on investor expectations of corporate profits:

$$Y_{it\rightarrow it+k} = \alpha + \beta X_{it} + \gamma Controls_{it} + u_{it+k}$$

with $k = 4, 8$ respectively, and the dependent variable, Y, equal to excess return and firm investment. X_{it} is our measure of expectations of corporate profits for each firm, i, in each quarter, t. We measure investor expectations of corporate profits, Rev_{it}, as the current revision in investors' expectations of next quarter corporate profits (Columns 1-4). The measure is constructed as the change between current and last period's investor expectations of next quarter corporate profits. To ease economic interpretation, the measures are re-scaled by their respective unconditional standard deviation. To refine identification, Columns 5-8 report results for 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}; and Columns 9-10 report results for a 2SLS-IV estimation that uses brokerage house mergers from Hong and Kacperczyk (2010) to instrument for Rev_{it}. Quarterly information on firm-level expectations is from IBES. The firm-level controls are size and current profitability (ROA). t-statistics are based on standard errors that are clustered at the firm level to allow for within-firm serial correlation.

Panel A: Excess Return on Corporate Bonds										
	Rev_{it}				Shock to Rev_{it}				Instrumented Rev_{it}	
	Full Sample		Crisis (2005-2010)		Full Sample		Crisis (2005-2010)		Full Sample	
	4-qtr	8-qtr	4-qtr	8-qtr	4-qtr	8-qtr	4-qtr	8-qtr	4-qtr	8-qtr
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
β	-0.212	-0.182	-0.284	-0.194	-0.030	-0.096	-0.150	-0.114	-0.244	-0.393
[t]	[-5.34]	[-3.28]	[-5.78]	[-3.88]	[-2.41]	[-3.93]	[-5.45]	[-3.89]	[-2.20]	[-3.18]
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	149,403	119,548	46,741	37,117	141,533	126,663	44,931	35,423	27,664	24,080
Bonds	4,118	3,513	1,660	1,349	4,027	3,728	1,630	1,322	1,001	950
R^2	0.18	0.13	0.15	0.12	0.13	0.13	0.14	0.12		

Panel B: Investment										
	Rev_{it}				Shock to Rev_{it}				Instrumented Rev_{it}	
	Full Sample		Crisis (2005-2010)		Full Sample		Crisis (2005-2010)		Full Sample	
	4-qtr	8-qtr	4-qtr	8-qtr	4-qtr	8-qtr	4-qtr	8-qtr	4-qtr	8-qtr
β	0.282	0.256	0.332	0.258	0.136	0.109	0.210	0.346	0.348	0.364
[t]	[25.88]	[24.62]	[9.74]	[7.93]	[7.91]	[6.05]	[6.95]	[7.78]	[3.31]	[3.70]
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	176,714	157,346	29,040	18,333	122,395	111,595	25,217	16,176	30,629	29,016
Firms	8,576	7,805	3,470	3,052	6,587	6,128	3,006	2,707	524	519
R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01		

Figure 1: Timing

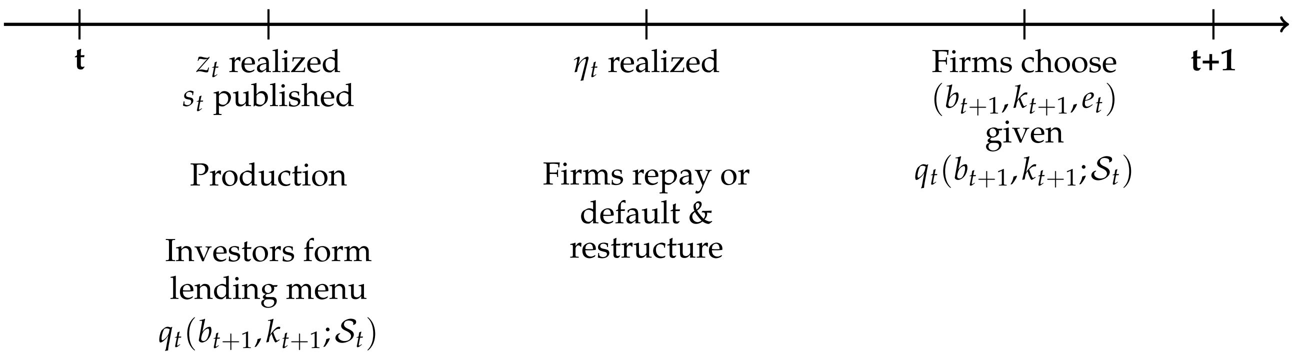
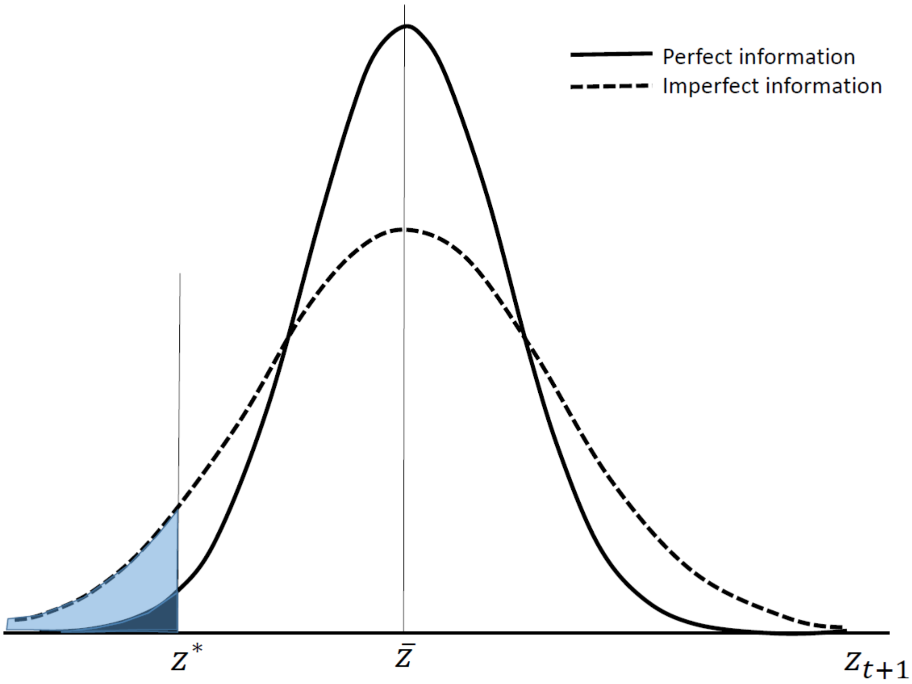
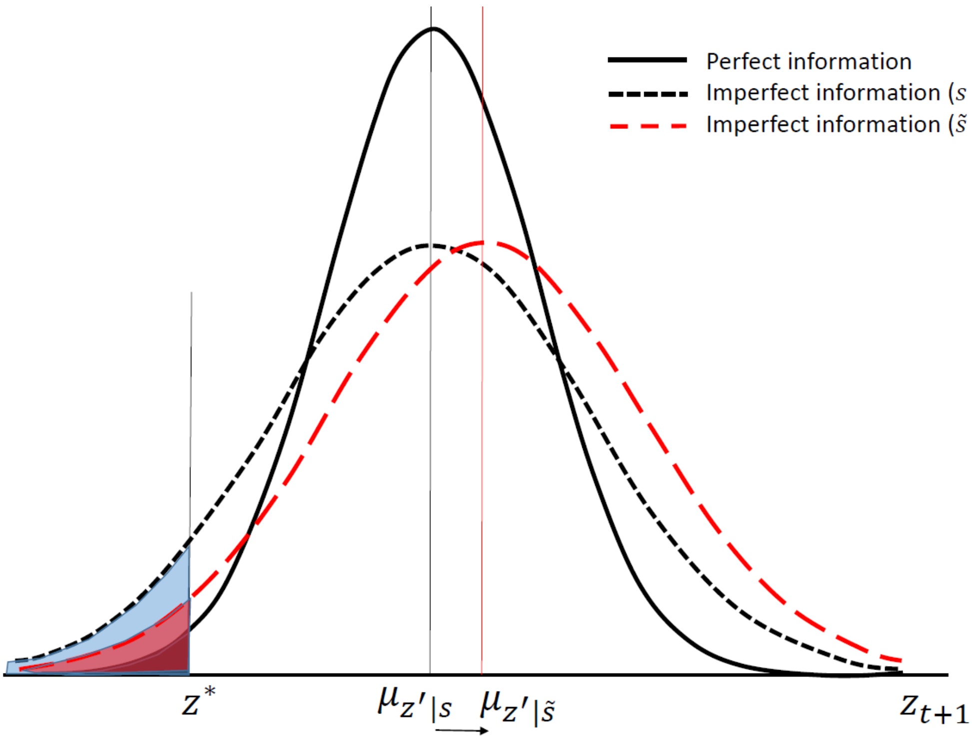


Figure 2: Impact of Information Frictions on Investors' Estimate of Default Probability

(a) Perfect vs. imperfect information



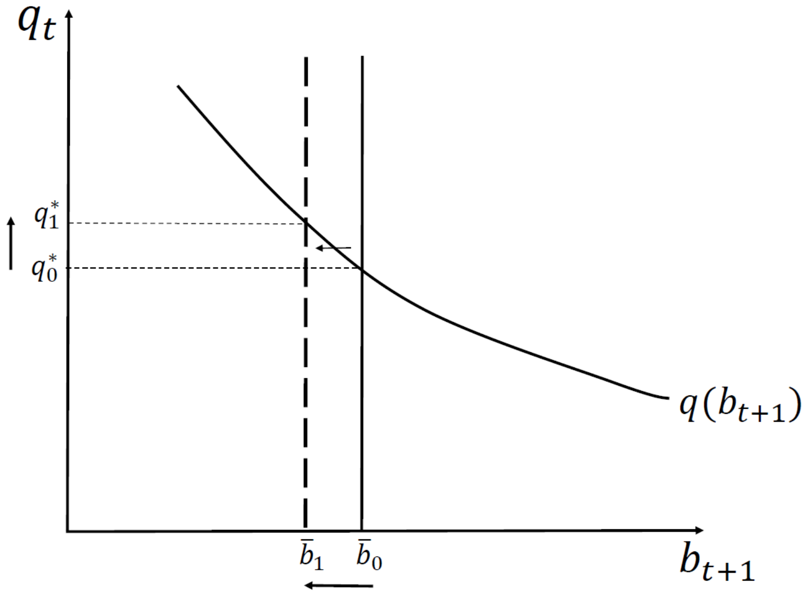
(b) Impact of signal under imperfect information



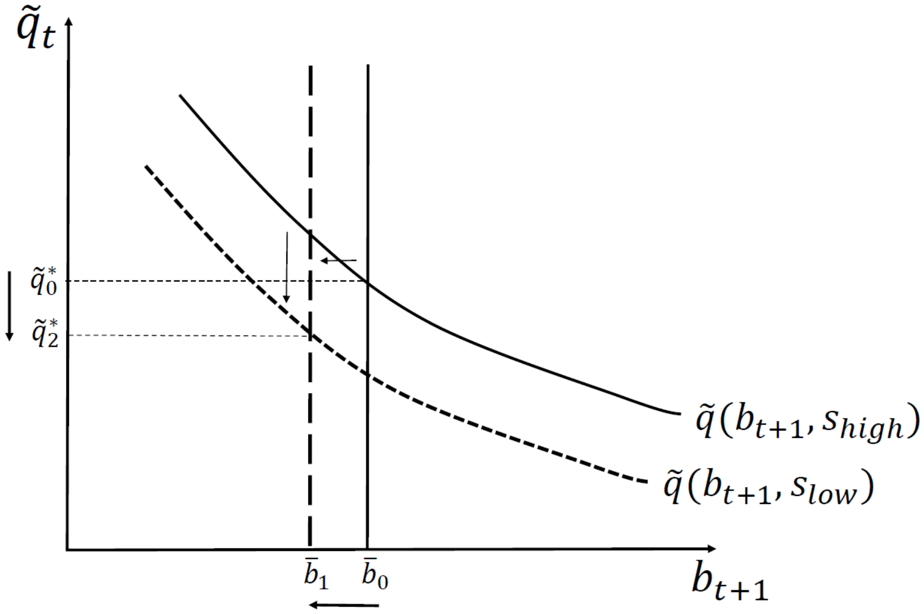
Note: The top panel plots the distribution of z_{t+1} conditional on z_t, $z_{t+1}|z_t \sim N\left(z_t, \sigma_\varepsilon^2\right)$ with $z_t = \bar{z}$ (solid line), as well as the distribution conditional on s_t, $z_{t+1}|s_t \sim N\left(\bar{z} + \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2+\sigma_u^2}(s_t - \bar{z}), 2\sigma_\varepsilon^2 - \frac{(\sigma_\varepsilon^2)^2}{\sigma_\varepsilon^2+\sigma_u^2}\right)$ with $s_t = \bar{z}$ (dotted line). The area to the left of z^* indicates the default probability under each distribution. The lower panel illustrates the impact of an increase in s_t on the conditional distribution (dashed line), where the conditional mean shifts from $\mu_{z|s}$ to $\mu_{z|\tilde{s}}$ with $\tilde{s}_t > s_t$.

Figure 3: Bond market equilibrium with & without information frictions

(a) Full information model



(b) Model with information frictions



Note: This figure is a simplified illustration of the determination of bond prices in a recession. If investors know the distribution of z_{t+1}, the price of bond is given by:

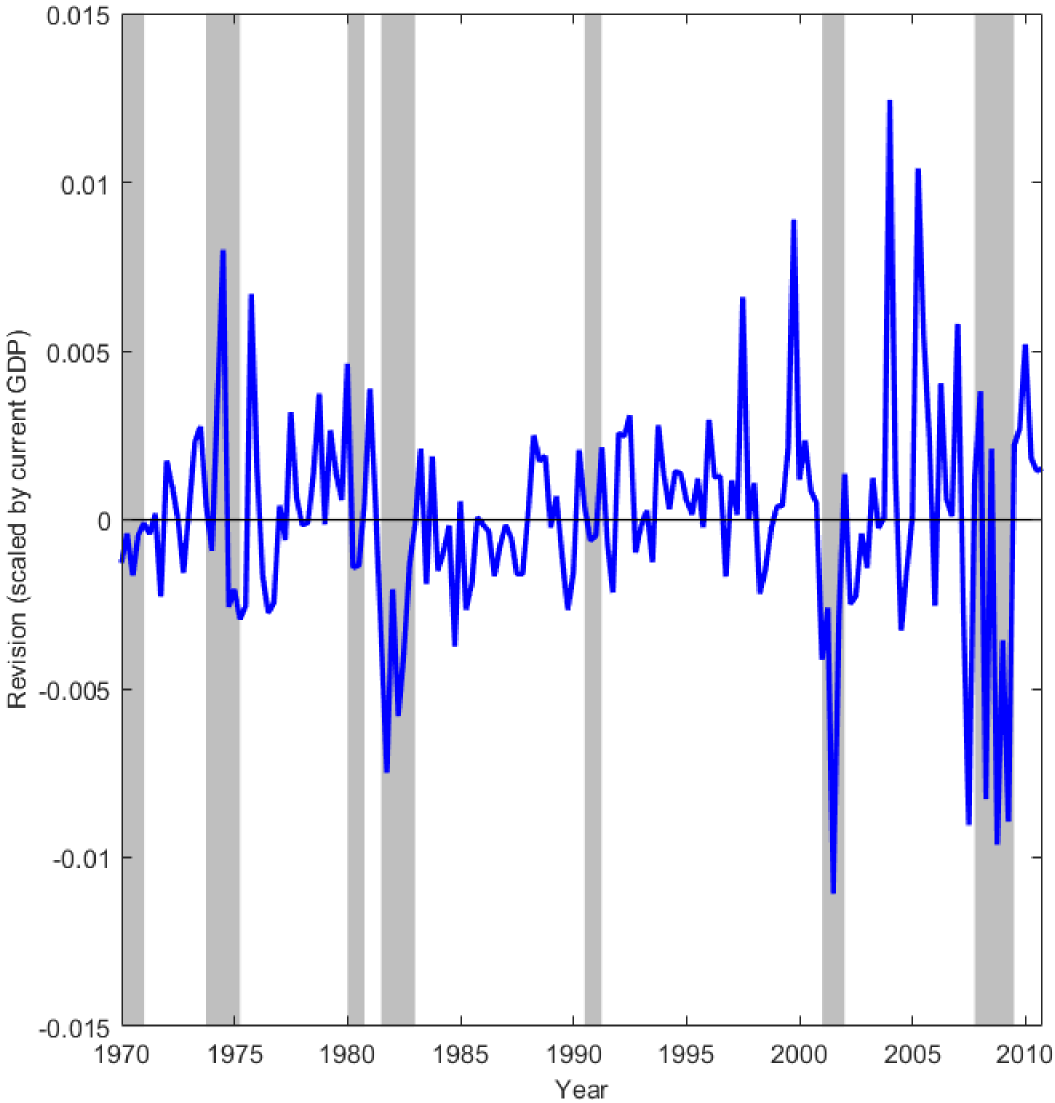
$$q_t = \beta\Big[1 - \Phi\Big(\frac{z^*(b_{t+1}) - z_t}{\sigma_\varepsilon}\Big)\Big].$$

If investors do not know the distribution of z_{t+1}, the price of bond follows:

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

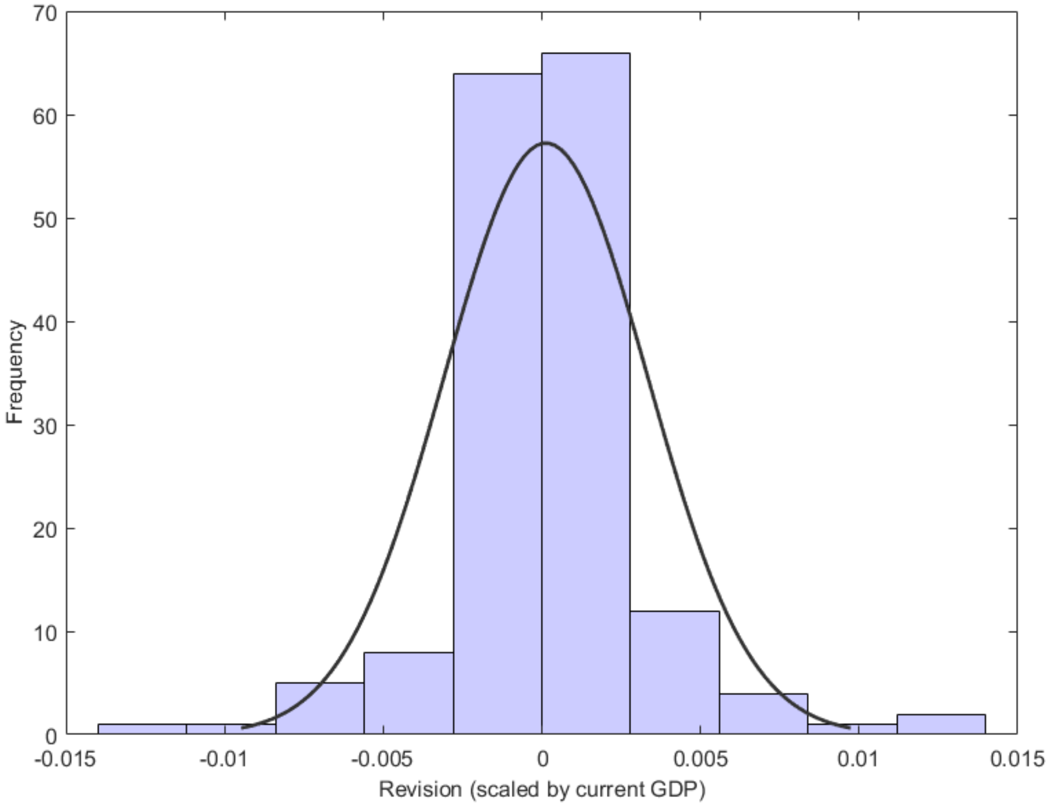
In both equations, the default threshold z^* is decreasing in the amount of bonds, $z^{*'}(b_{t+1}) < 0$. In a recession driven by negative shocks to profitability, the firm's credit demand shifts from $\bar{b}_0$ to $\bar{b}_1$. Hence the equilibrium bond price rises to q_1^* in the full information model (Panel (a)). If investors receive pessimistic signals in a recession, the bond pricing schedule simultaneously shifts down to $q(\bar{p}, s_{\text{low}})$. The equilibrium bond price falls to q_2^* in the model with information frictions.

Figure 4: Current Revision in Investors' Expectations of Next Quarter Corporate Profits from the Survey of Professional Forecasters



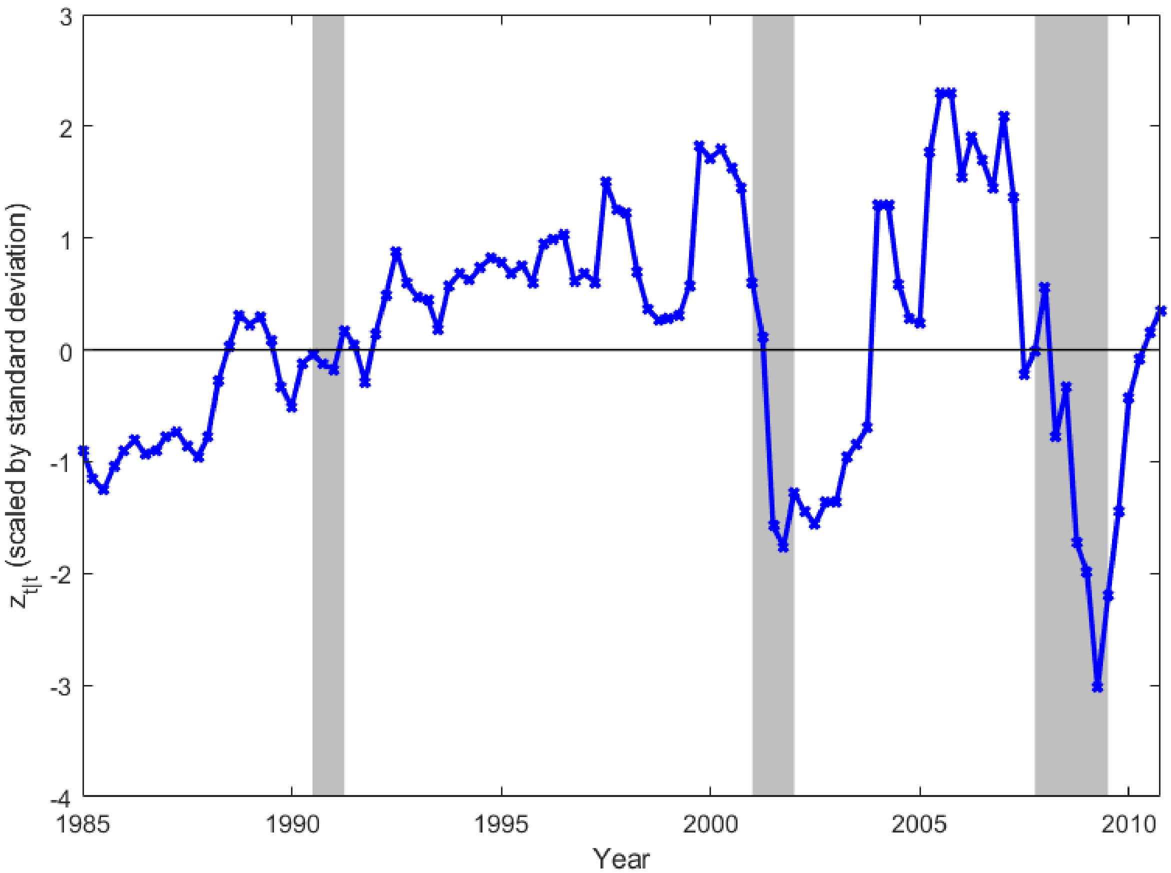
Note: This figure shows the current revision in investors' expectations of next quarter's corporate profit between 1970Q1 and 2010Q4, divided by the current GDP. Data is from the Survey of Professional Forecasters. Shaded areas indicate the NBER recession dates.

Figure 5: Distribution of the Revision Series



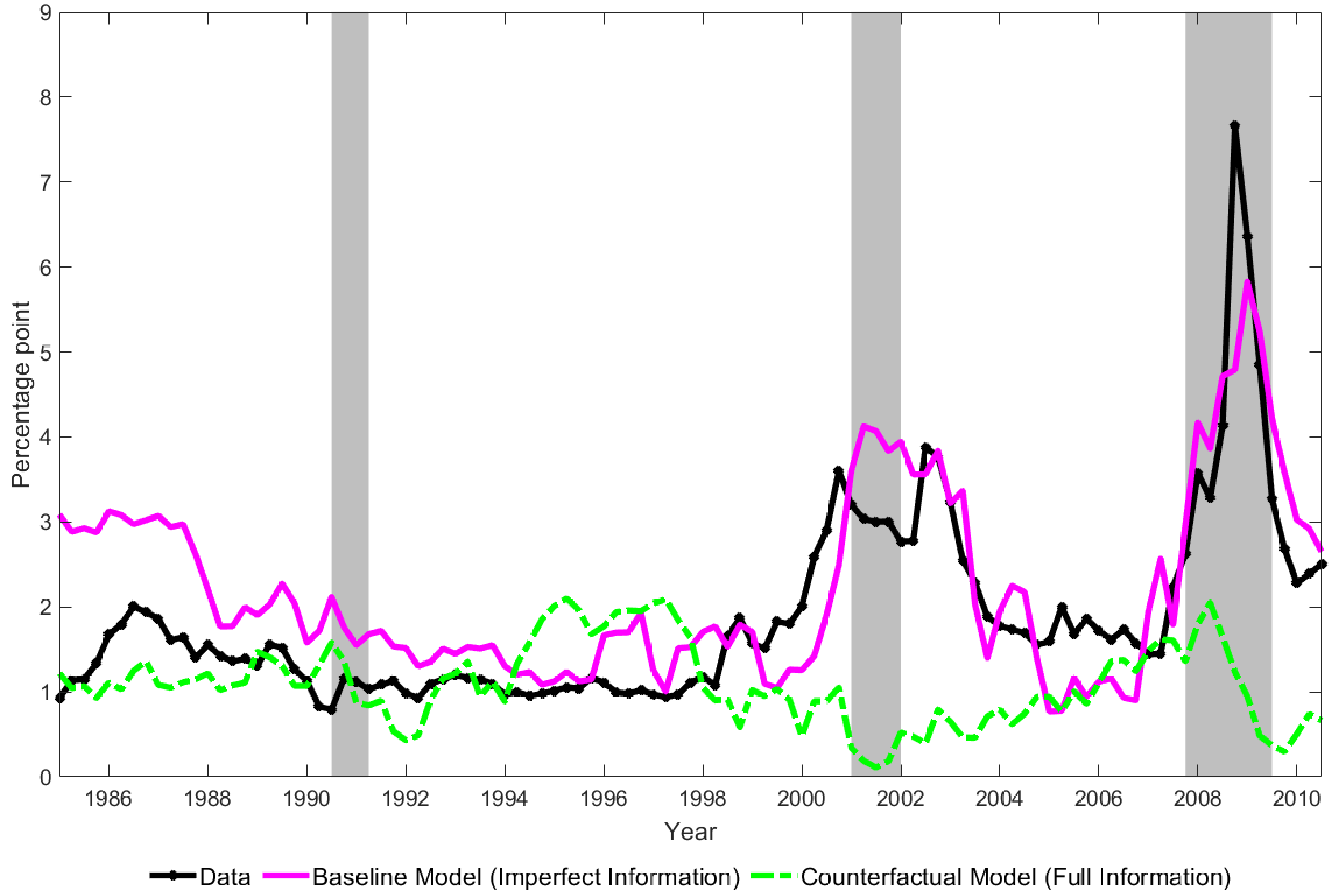
Note: This histogram shows the distribution of the signal – the current revision in investors' expectations of next quarter's corporate profit as a fraction of US GDP – between 1970Q1 and 2010Q4. Data is from the Survey of Professional Forecasters. The Kolmogorov-Smirnov test statistic for the sample has a p-value of 0.126.

Figure 6: Debt Investors' Estimate of the Unobserved State (1985Q1-2010Q4)



Note: This figure shows the debt investors' estimate of z_t (scaled by the standard deviation) in a state-space model: the state equation is (A.1) and the measurement equation is (A.2). The Kalman filter uses data on current revisions in investors' expectations of next quarter corporate profits from the Survey of Professional Forecasters (scaled by total assets) from 1970Q1 to the current period. Shaded areas indicate the NBER recession dates.

Figure 7: Historical Bond Spread: Data vs. Model (1985Q1–2010Q4)



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 two different model-implied series: one from the imperfect information model with learning (purple line), and the other from the model without information frictions (green line). In this exercise, we feed the realized profit shocks (z_t) and revisions as signals (s_t) into our model simulations. Shaded areas indicate the NBER recession dates.

The Information Driven Financial Accelerator Online Appendix

November 2020

A Computation

A.1. Estimating the unobserved state using the revision series

We can rewrite the model consisting of equations (3) and (6) in state-space form. The state equation is:

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

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:

$$s_t = C\alpha_t + u_t \tag{A.2}$$

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 $(\alpha_1, ..., \alpha_T, s_1, ..., s_T)$ is normally distributed. We introduce the following notation:

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

In our model, the problem faced by the 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:

$$s_{t|t-1} = C\alpha_{t|t-1} \tag{A.3}$$

$$G_t = CP_{t|t-1}C' + \sigma_u^2 \tag{A.4}$$

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

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

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

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

where Q is the covariance matrix of η_t. Then we go back to (A.3) and (A.4) 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 (Figure 4). We then use these values to jointly solve the firm's problem and the debt market equilibrium.

A.2. Solving the firm's problem

Recall that the processes for z_t and s_t are given by (3) and (6), respectively. We transform z_t (3) into discrete-state Markov chains in the range $\left[-4\sigma_\varepsilon/\sqrt{1-\rho_z^2}, 4\sigma_\varepsilon/\sqrt{1-\rho_z^2}\right]$, using the method in Tauchen (1986). We discretize s_t in the range $\left[-4\sigma_s, 4\sigma_s\right]$, and η_t in the range $\left[-3\sigma_\eta, 3\sigma_\eta\right]$. Furthermore, we create equispaced grids for capital (k_t), bond (b_t), the conditional mean of z_t ($z_{t|t}$) and the conditional variance ($\Omega_{t|t}$). We determine the upper and lower bounds of the grids for $z_{t|t}$ and $\Omega_{t|t}$ by running a Kalman filter using the signal series, as described in Section A.1. To simplify notation, let:

$$\hat{z}_{t-1} \equiv z_{t-1|t-1}$$
$$\hat{\Omega}_{t-1} \equiv \Omega_{t-1|t-1}$$

The state variables of a firm are $\left(k_t, b_t, z_t, \eta_t, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1}\right)$, where $\hat{z}_{t-1}$ and $\hat{\Omega}_{t-1}$ are the first two moments of the conditional normal distribution (conditional on the history $\mathcal{S}_{t-1}$). Due to the equity issuance cost in the value function (8), η_t is a state variable despite being i.i.d. across time. We evaluate the continuation values off the grid points using multidimensional spline interpolation, solve the model via iteration on the Bellman equation using the following procedure.

1. Guess $V(k_t, b_t, z_t, \eta_t, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1})$, and denote it as $V^0(k_t, b_t, z_t, \eta_t, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1})$. Guess $q_t(k_{t+1}, b_{t+1}, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1})$, and denote it as $q_t^0(k_{t+1}, b_{t+1}, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1})$;
2. Given $V^0(k_t, b_t, z_t, \eta_t, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1})$, compute $J^0(k_t, b_t, z_t, \eta_t, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1})$ using (7),

such that J is bounded below at zero.

3. Given $q_t^0(k_{t+1}, b_{t+1}, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1})$, compute equity payout / dividend $e_t^0(k_t, b_t, b_{t+1}, k_{t+1}, z_t, \eta_t, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1})$ using (10), and equity issuance cost $\Lambda(e_t^0)$ using (5);

4. Given $J^0(k_{t+1}, b_{t+1}, z_{t+1}, \eta_{t+1}, s_{t+1}, \hat{z}_t(s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1}), \hat{\Omega}_t(\hat{\Omega}_{t-1}))$, $q_t^0(k_{t+1}, b_{t+1}, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1})$, $e_t^0(k_t, b_t, b_{t+1}, k_{t+1}, z_t, \eta_t, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1})$, and $\Lambda(e_t^0)$, find the value function $V^1(k_t, b_t, z_t, \eta_t, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1})$ and the associated policy functions $b_{t+1}^{*0}(k_t, b_t, z_t, \eta_t, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1})$ and $k_{t+1}^{*0}(k_t, b_t, z_t, \eta_t, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1})$ that satisfy the maximization problem (8);

5. Using the guess $q_t^0(k_{t+1}, b_{t+1}, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1})$, find $q_{t+1}^0\Big(b_{t+2}, k_{t+2}, s_{t+1}, \hat{z}_t\big(s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1}\big), \hat{\Omega}_t\big(\hat{\Omega}_{t-1}\big)\Big)$ – or $q_{t+1}^0\big(b_{t+1}, k_{t+1}, s_{t+1}, z_{t+1}, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1}\big)$ – where $b_{t+2}\Big(k_{t+1}, b_{t+1}, z_{t+1}, \eta_{t+1}, s_{t+1}, \hat{z}_t\big(s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1}\big), \hat{\Omega}_t\big(\hat{\Omega}_{t-1}\big)\Big)$ and $k_{t+2}\Big(k_{t+1}, b_{t+1}, z_{t+1}, \eta_{t+1}, s_{t+1}, \hat{z}_t\big(s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1}\big), \hat{\Omega}_t\ \big(\hat{\Omega}_{t-1}\big)\Big)$ are consistent with the policy functions from step 4;[12]

6. Using $V^0\Big(k_{t+1}, b_{t+1}, z_{t+1}, \eta_{t+1}, s_{t+1}, \hat{z}_t(s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1}), \hat{\Omega}_t(\hat{\Omega}_{t-1})\Big)$, and $q_{t+1}^0\big(b_{t+1}, k_{t+1}, s_{t+1}, z_{t+1}, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1}\big)$, compute the recovery value of bond $B^0(b_{t+1}, k_{t+1}, z_{t+1}, \eta_{t+1}, s_{t+1}, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1})$ according to (12);

7. Find the right-hand side of equation (11) using $q_{t+1}^0\big(b_{t+1}, k_{t+1}, s_{t+1}, z_{t+1}, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1}\big)$, and $B^0(b_{t+1}, k_{t+1}, z_{t+1}, \eta_{t+1}, s_{t+1}, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1})$. This gives the market clear bond price and denote it as $q_t^1(b_{t+1}, k_{t+1}, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1})$. We compute the conditional normal density $\tilde{f}(z_{t+1}|\mathcal{S}_t)$

$$= \frac{1}{\hat{\Omega}_t\big(\hat{\Omega}_{t-1}\big)\sqrt{2\pi}} \exp\Big(-\frac{1}{2}\Big(\frac{z_{t+1} - \hat{z}_t\big(s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1}\big)}{\hat{\Omega}_t\big(\hat{\Omega}_{t-1}\big)}\Big)\Big)$$

on the multi-dimensional grid over s_t, $\hat{z}_{t-1}$, $\hat{\Omega}_{t-1}$ and z_{t+1}. We then use the Newton-Cotes quadrature for numerical integration;

8. Updating:

   - Update our guess for the value function $V^0(k_t, b_t, z_t, \eta_t, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1})$ to $V^1(k_t, b_t, z_t, \eta_t, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1})$;
   - Update our guess $q_t^0(b_{t+1}, k_{t+1}, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1})$ to $q_t^1(b_{t+1}, k_{t+1}, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1})$;

[12] With long-term debt, the price of debt depends on future debt prices q_{t+1} and thus on next period's leverage and investment choices (b_{t+2}, k_{t+2}). Time consistency requires that next period's leverage and investment decisions be functions of the current policy.

9. Repeat steps 2-8 until convergence, i.e. the following conditions are jointly satisfied, for $\varepsilon \approx 0$:

$$\left| V^{T+1}(k_t, b_t, z_t, \eta_t, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1}) - V^{T}(k_t, b_t, z_t, \eta_t, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1}) \right| < \varepsilon;$$

$$\left| q_t^{T+1}(b_{t+1}, k_{t+1}, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1}) - q_t^{T}(b_{t+1}, k_{t+1}, s_t, \hat{z}_{t-1}, \hat{\Omega}_{t-1}) \right| < \varepsilon.$$

A.3. Solving the General Equilibrium Model

We introduce a general equilibrium version of our baseline model in Section 6. The firm's problem is solved according to the procedure above, but we add an "outer loop" to our algorithm to solve for market clearing. Specifically, we start with guesses for aggregate consumption C_t^0 and laws of motion for firm capital Γ_K^0 and debt Γ_B^0, respectively, as functions of the state variables. Given these guesses, we can compute the household's stochastic discount factor for pricing financial assets. Then we solve the firm's problem and equilibrium bond prices following the procedure outlined above ("inner loop"). Check if the market clearing conditions are satisfied, given the policy functions for investment, labor, and our initial guess C_t^0; if not, adjust our guess for consumption to C_t^1. We also need to update the guessed laws of motion for capital Γ_K^0 and debt Γ_B^0 using the policy functions for investment and borrowing, before solving the firm's problem again. Repeat this procedure until the market clearing conditions are satisfied.

A.4. Simulation

Our baseline model features heterogeneous firms receiving idiosyncratic revenue shocks. The model-implied moments are based on 2,000 quarters (after dropping the first 200) of simulated data for 5,000 firms, where the aggregate and idiosyncratic shocks ε_t^z and η_t are randomly drawn. The default rate is the fraction of defaulting firms. In order to maintain tractability, the general equilibrium model features a representative firm, and we simulate it for 10,000 periods. The default rate in the GE model is the number of times the firm defaults over the total number of periods. Recall that default is followed by restructuring (subject to a deadweight loss) and not firm exit in the model.

B Derivations for Results in Section 4

In this section we provide the proofs for Results 1, 2 and 3 in Section 4.

1. It is immediate from equation (15) that:

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

   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

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

   so equation (15) becomes $\tilde{q}_t = \beta\Big[1 - \Phi(A)\Big]$. We can show that:

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

   If the default threshold z^* is sufficiently low:

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

   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:

$$q_t = \beta\Big[1 - \Phi\Big(\frac{z^* - \bar{z}}{\sigma_\varepsilon}\Big)\Big] \tag{A.5}$$

$$\tilde{q}_t = \beta\left[1 - \Phi\left(\frac{z^* - \bar{z}}{\sqrt{\sigma_z^2 + \sigma_\varepsilon^2 - \frac{(\sigma_z^2)^2}{\sigma_z^2 + \sigma_u^2}}}\right)\right] \tag{A.6}$$

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.6) is smaller than q_t in (A.5), for all $z^* < \bar{z}$.

C Model with Perfect Information

B.1. Main differences from the baseline model

If bond investors can perfectly observe z_t, then the bond pricing function q_t simplifies to:

$$q(b_{t+1},k_{t+1},z_t) = \beta\Bigg[\int \Phi\big(\eta^*_{t+1}(k_{t+1},b_{t+1},z_{t+1})\big)\Big[c+\lambda+(1-\lambda)q_{t+1}\big(b_{t+2},k_{t+2};\mathcal{S}_{t+1}\big)\Big]dF(z_{t+1}|z_t) + \iint_{\eta_{t+1}>\eta^*_{t+1}(k_{t+1},b_{t+1},z_{t+1})} B(b_{t+1},k_{t+1},z_{t+1},\eta_{t+1})d\Phi(\eta_{t+1})dF(z_{t+1}|z_t)\Bigg], \tag{A.7}$$

where $\eta^*_{t+1}(k_{t+1},b_{t+1},z_{t+1})$ is the default threshold pinned down by the condition:

$$J(k_{t+1},b_{t+1},z_{t+1},\eta^*_{t+1}) = 0.$$

As before, $B(b_{t+1},k_{t+1},z_{t+1},\eta_{t+1})$ is the recuperation rate of bond that takes the value between 0 and the maximum recovery rate $B_{\max}$:

$$B(b_{t+1},k_{t+1},z_{t+1},\eta_{t+1}) = \min\Bigg[\max\Big[0,\ \Big((1-\tau)\big(z_{t+1}k^{\alpha}_{t+1}-\eta_{t+1}\big)+V(k_{t+1},b_{t+1},z_{t+1},\eta_{t+1}) + (1-\lambda)q(b_{t+2},k_{t+2},z_{t+1})b_{t+1}-\xi k_{t+1}\Big)\frac{1}{b_{t+1}}\Big],\ B^{\max}\Bigg]. \tag{A.8}$$

The equity value of the firm is:

$$J(k_t,b_t,z_t,\eta_t) = \max\Big[0,\ (1-\tau)\big(z_tk^{\alpha}_t-\eta_t\big)-(c+\lambda)b_t+\tau\big(\delta k_t+cb_t\big)+V(k_t,b_t,z_t,\eta_t)\Big], \tag{A.9}$$

where

$$V(k_t,b_t,z_t,\eta_t) = \max_{b_{t+1},k_{t+1},e_t}\Bigg\{q_t\Big(b_{t+1}-(1-\lambda)b_t\Big)-\Big(k_{t+1}-(1-\delta)k_t\Big)-g(k_t,k_{t+1})+\Lambda(e_t) + \beta\Big[\iint_{\eta_{t+1}\le\eta^*_{t+1}(k_{t+1},b_{t+1},z_{t+1})} J\big(k_{t+1},b_{t+1},z_{t+1},\eta_{t+1}\big)\Big]d\Phi(\eta_{t+1})dF(z_{t+1}|z_t)\Bigg\}. \tag{A.10}$$

The definition of equity payout / issuance is:

$$e_t(k_t,b_t,z_t,\eta_t,k_{t+1},b_{t+1}) = (1-\tau)\big(z_t k_t^{\alpha} - \eta_t\big) - \big(c+\lambda\big)b_t - \big(k_{t+1} - (1-\delta)k_t\big) - g\big(k_t,k_{t+1}\big) + \tau\big(\delta k_t + c b_t\big) + q(b_{t+1},k_{t+1},z_t)\Big(b_{t+1} - (1-\lambda)b_t\Big). \quad \text{(A.11)}$$

The investment adjustment cost $g(k_t,k_{t+1})$ and equity issuance cost $\Lambda(e_t)$ follow (4) and (5), respectively.

B.2. Algorithm

The algorithm for solving the full information model is standard, and with fewer state variables (k_t,b_t,z_t,η_t):

1. Guess $V(k_t,b_t,z_t,\eta_t)$, and denote it as $V^0(k_t,b_t,z_t,\eta_t)$. Guess $q_t(b_{t+1},k_{t+1},z_t)$, and denote it as $q_t^0(b_{t+1},k_{t+1},z_t)$;

2. Given $V^0(k_t,b_t,z_t,\eta_t)$, compute $J^0(k_t,b_t,z_t,\eta_t)$ using (A.9), such that J is bounded below at zero. Given $q_t^0(b_{t+1},k_{t+1},z_t)$, compute equity payout / dividend $e_t^0(k_t,b_t,b_{t+1},k_{t+1},z_t,\eta_t)$ using (A.11), and equity issuance cost $\Lambda\big(e_t^0\big)$ using (5);

3. Given $q_t^0(b_{t+1},k_{t+1},z_t)$, $e_t^0(k_t,b_t,b_{t+1},k_{t+1},z_t,\eta_t)$, $\Lambda\big(e_t^0\big)$ and $J^0(k_{t+1},b_{t+1},z_{t+1},\eta_{t+1})$, find the value function $V^1(k_t,b_t,z_t,\eta_t)$ and the associated policy functions $b_{t+1}^{*0}(k_t,b_t,z_t,\eta_t)$ and $k_{t+1}^{*0}(k_t,b_t,z_t,\eta_t)$ that satisfy the maximization problem (A.10);

4. Find $q_{t+1}^0\big(b_{t+2},k_{t+2},z_{t+1}\big)$ – or $q_{t+1}^0\big(b_{t+1},k_{t+1},z_{t+1}\big)$ – where $b_{t+2}(k_{t+1},b_{t+1},z_{t+1})$ and $k_{t+2}(k_{t+1},b_{t+1},z_{t+1})$ are consistent with the policy functions from step 4, using the guess $q_t^0(b_{t+1},k_{t+1},z_t)$;

5. Using $V^0(k_{t+1},b_{t+1},z_{t+1},\eta_{t+1})$ and $q_{t+1}^0(b_{t+1},k_{t+1},z_{t+1})$, compute the recovery value of bond $B^0(b_{t+1},k_{t+1},z_{t+1},\eta_{t+1})$ according to (A.8);

6. Find $q_t(b_{t+1},k_{t+1},z_t)$ that satisfies (A.7) using $q_{t+1}^0\big(b_{t+2},k_{t+2},z_{t+1}\big)$ and $B^0(b_{t+1},k_{t+1},z_{t+1},\eta_{t+1})$ from steps 5 and 6, respectively. Denote it as $q_t^1(b_{t+1},k_{t+1},z_t)$;

7. Updating:

   - Update our guess for the value function $V^0(k_t,b_t,z_t,\eta_t)$ to $V^1(k_t,b_t,z_t,\eta_t)$;
   - Update our guess for the bond price $q_t^0(b_{t+1},k_{t+1},z_t)$ to $q_t^1(b_{t+1},k_{t+1},z_t)$;

8. Repeat steps 2-7 until convergence.

D Alternative Learning Rules

Here we extend our baseline model and consider three types of behavioral biases that distort investors' expectations of the firm's latent state, and we use the model to quantify the relative contribution of different mechanisms that drive credit cycles. First, we consider the case where agents' beliefs are systematically biased toward either the "good" or the "bad" states, depending on whether they are optimistic or pessimistic. Then we consider near-rational learning, in which the investors still update their beliefs about the latent state using the Bayes' rule but they make random mistakes. Lastly, we also consider the model implications when investors overextrapolate, i.e. they believe the signal is more persistent than it actually is. Table A.7 summarizes the model-implied moments under these alternative learning rules.

Optimism and Pessimism

In our context, investors are "pessimistic" (or "optimistic") if their estimate of the unobserved state is systematically lower (higher) than the estimate of an investor who learns rationally. For tractability, we capture the notion of biased beliefs in a reduced-form fashion by assuming that for a given history $\mathcal{S}_t$, they update their belief about z_t according to:

$$z_{t|t}^{\text{bias}} = z_{t|t} + \psi, \tag{A.12}$$

where ψ is a constant and $z_{t|t}$ is from the rational learning model. We use $\psi_p < 0$ for pessimistic investors, and $\psi_o > 0$ for optimistic investors.

To calibrate ψ_p and ψ_o, we re-parameterize the model, and use them to target the historical average default rates for firms issuing high-yield bonds and investment-grade bonds, respectively.[13] Thus, we solve the model under two sets of parameterization, one for each type of firms. We target the same moments as in the baseline model (default rate and its volatility, profit-to-asset ratio, leverage ratio, investment rate), except now we distinguish between investment-grade and speculative-grade firms. Tables A.5 and A.6 summarize the parameter values in each set of calibration. Columns (3) and (4) of Table A.7 report the model predictions of the aggregate moments and their data counterparts.

The model with pessimistic investors produces higher and more volatile spreads than the model with optimistic investors, which are patterns consistent with the data on high-yield corporate bonds and investment-grade bonds, respectively. For instance, the spread between high-yield and investment-grade is 3.42% in the data, and 2.71% in the model. Moreover, introducing biased beliefs does not overturn the model prediction that spreads are countercyclical.

[13]The other internally calibrated parameters are μ_η, σ_η, c_k, and c_e. Here we externally calibrate the bankruptcy cost ξ using a commonly used value from the literature.

Near Rational Learning

Suppose that investors update their beliefs about the hidden state using Bayes' rule, but occasionally, they make mistakes. As long as the mistakes are random, their subjective belief about the current state z_t is still conditionally unbiased. For a given history $\mathcal{S}_t$, investors update their belief about z_t according to:

$$z_{t|t}^{\mathrm{NR}} = (1-\omega)z_{t|t} + \omega\sigma_v v_t, \tag{A.13}$$

where $z_{t|t}$ is from the rational learning model, v_t is an i.i.d. error from a standard normal distribution, and ω is a weighting parameter in $[0,1]$. For comparative statics, we choose two different values for ω: $\omega = 0.1$ and $\omega = 0.3$, i.e. investors are rational 90% and 70% of the time, respectively.

Columns (5) and (6) of Table A.7 shows that with near-rational investors, credit spreads and investment become significantly more volatile, but the mean levels do not change much. As investors receive a random error in each period, the error could bias their belief about a certain state either upward or downward, so on average, these errors do not have significant impact on the levels of spread and investment, but unambiguously increase their volatilities, especially if investors make mistakes more often.

Overextrapolation

In our context, extrapolative investors believe firm profitability to be more persistent than it actually is. Formally, they believe the profitability persistence parameter in equation (3) to be $\rho_z^B > \rho_z$. This then affects their estimate of the unobserved state in the Kalman filter.

Let $\zeta = \rho_z^B/\rho_z - 1$ measure the degree of overextrapolation. Like in the near-rational learning case, we perform comparative statics analysis by calibrating two different values for ζ in turn, while keeping the other parameter values the same as in the baseline model with rational learning (Table 4).

Quantitatively, the last two columns of Table A.7 illustrate that augmenting the rational learning model with overextrapolation improves the model fit on some aggregate moments, such as the business cycle correlations. For instance, the baseline model can account for approximately 45% of the correlation between spread and output in the data, whereas with 15% overextrapolation, the model can account for about 59% of it. Similarly, the baseline model can account for approximately 38% of the correlation between default and output in the data, whereas the model with overextrapolation can account for about 62% of it.

E Additional Tables and Figures

Table A.1: Multivariate Forecasting Regressions of Credit Spreads: Additional Outcomes

This table summarizes additional robustness results of multivariate time-series forecasting regressions of excess bond returns on investor expectations of corporate profits, controlling for 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), the term spread, and lagged excess returns:

$$R_{t\rightarrow t+k} = \alpha + \beta X_t + \gamma Controls_t + u_{t+k}$$

X_t is our measure of expectations of corporate profits and its noise, in turn, in each quarter. We measure investor expectations of corporate profits, Rev_t, as the current revision in investors' expectations of next quarter corporate profits. The measure is contructed 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, 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 is from the Survey of Professional Forecasters. In Panel A, the dependent variable is the 1-, 2-, 3-, 4- or 8-quarter cumulative excess return on corporate bonds. In Panel B, the dependent variable is the 1-, 2-, 3-, 4- or 8-quarter cumulative excess return on BBB-minus rated corporate bonds relative to AAA-rated bonds. In Panel C, the dependent variable is the 1-, 2-, 3-, 4- or 8-quarter cumulative excess bond premium by Gilchrist and Zakrajšek (2012). t-statistics for k-period forecasting regressions are based on Newey-West (1987) standard errors allowing for serial correlation up to k-1 lags, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: Excess Return on Corporate Bonds										
	Rev_t					σ_t				
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
β	-0.143	-0.105	-0.100	-0.064	-0.060	0.242	0.261	0.291	0.343	0.520
[t]	[-2.78]	[-2.28]	[-3.00]	[-2.08]	[-2.41]	[3.18]	[3.23]	[3.26]	[3.06]	[4.67]
R^2	0.77	0.81	0.83	0.84	0.87	0.78	0.76	0.72	0.69	0.66
Panel B: Excess Return on BAA-Rated Corporate Bonds										
	Rev_t					σ_t				
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
β	-0.051	-0.027	-0.027	-0.022	-0.024	0.155	0.148	0.150	0.165	0.214
[t]	[-2.22]	[-1.31]	[-1.74]	[-1.43]	[-2.42]	[4.74]	[4.32]	[3.79]	[3.51]	[5.72]
R^2	0.67	0.70	0.74	0.76	0.85	0.69	0.72	0.73	0.73	0.77
Panel C: Excess Corporate Bond Premium										
	Rev_t					σ_t				
	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
β	-0.095	-0.067	-0.050	-0.038	-0.032	0.013	0.014	0.030	0.058	0.133
[t]	[-3.52]	[-3.10]	[-2.73]	[-2.10]	[-1.73]	[0.31]	[0.37]	[0.64]	[0.95]	[2.19]
R^2	0.47	0.56	0.58	0.57	0.57	0.59	0.61	0.54	0.46	0.39

Table A.2: Additional Business Cycle Outcomes

This table summarizes additional robustness results of multivariate time-series forecasting regressions of business cycle aggregates on the component of excess bond returns that is predictable based on investor expectations of corporate profits, controlling for 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), the term spread:

$$BC_{t\to t+k} = \alpha + \beta \widehat{R}_{t-\to t+k} + \gamma Controls_t + u_{t+k}$$

$\widehat{R}_{t\to t+k}$ is estimated from the multivariate forecasting regression of credit spreads, $R_{t\to t+k} = \alpha + \beta X_t + \gamma Controls_t + u_{t+k}$, where X_t is our measure of expectations of corporate profits and its noise, in turn, in each quarter. We measure investor expectations of corporate profits, Rev_t, as the current revision in investors' expectations of next quarter corporate profits. The measure is contructed 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, 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 is from the Survey of Professional Forecasters. In Panel A, $\widehat{R}_{t\to t+k}$ is the predicted 4- or 8-quarter cumulative excess return on corporate bonds. In Panel B, $\widehat{R}_{t\to t+k}$ is the predicted 4- or 8-quarter cumulative excess return on BBB-minus rated corporate bonds relative to AAA-rated bonds. In Panel C, $\widehat{R}_{t\to t+k}$ is the predicted 4- or 8-quarter cumulative excess bond premium by Gilchrist and Zakrajšek (2012). Robust t-statistics are shown in brackets, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: Excess Return on Corporate Bonds								
	Rev_t				σ_t			
	Emp 4-qtr	Emp 8-qtr	Cons 4-qtr	Cons 8-qtr	Emp 4-qtr	Emp 8-qtr	Cons 4-qtr	Cons 8-qtr
β	-0.319	-0.329	0.132	-0.067	-0.551	-0.437	-0.235	-0.194
[t]	[-1.56]	[-3.08]	[0.031]	[-0.35]	[-8.00]	[-10.90]	[-3.10]	[-3.58]
R^2	0.71	0.75	0.36	0.40	0.70	0.76	0.43	0.39
Panel B: Excess Return on BAA-Rated Corporate Bonds								
	Rev_t				σ_t			
	Emp 4-qtr	Emp 8-qtr	Cons 4-qtr	Cons 8-qtr	Emp 4-qtr	Emp 8-qtr	Cons 4-qtr	Cons 8-qtr
β	-1.038	-0.991	0.428	-0.204	-1.224	-1.094	-0.522	-0.485
[t]	[-1.26]	[-1.76]	[0.29]	[-0.37]	[-6.41]	[-7.98]	[-2.86]	[-3.44]
R^2	0.52	0.51	0.37	0.40	0.47	0.48	0.36	0.40
Panel C: Excess Corporate Bond Premium								
	Rev_t				σ_t			
	Emp 4-qtr	Emp 8-qtr	Cons 4-qtr	Cons 8-qtr	Emp 4-qtr	Emp 8-qtr	Cons 4-qtr	Cons 8-qtr
β	-0.635	-0.739	0.262	-0.129	-3.535	-2.041	-1.507	-0.904
[t]	[-1.24]	[-1.73]	[0.32]	[-0.32]	[-1.98]	[-3.99]	[-1.83]	[-3.61]
R^2	0.62	0.64	0.37	0.40	0.08	0.09	0.18	0.20

Table A.3: Model without Equity Financing

Panel A: Targeted moments	**Data**	**With equity**	**Without equity**
	(1)	(2)	(3)
Investment rate (mean)	0.018	0.022	0.017
Leverage (mean)	0.267	0.291	0.298
Profit to asset (mean)	0.053	0.068	0.049
Default rate	0.013	0.016	0.018
σ(default)	0.012	0.013	0.016
Panel B: Untargeted moments	**Data**	**With equity**	**Without equity**
	(1)	(2)	(3)
Bond spread (mean)	0.019	0.021	0.024
σ(spread)	0.011	0.018	0.020
Corr(spread, output)	-0.573	-0.259	-0.196
Corr(default, output)	-0.431	-0.163	-0.142
σ(invest)/σ(output)	3.458	2.394	2.552
Corr(invest, output)	0.574	0.890	0.896

Note: This table compares the model-generated moments in the model with (baseline) and without equity financing (counterfactual). Panel A reports the targeted moments, and Panel B reports the untargeted fit of the model. The data moments are calculated from Compustat. The model-implied moments are based on 2,000 quarters of simulated data for 5,000 firms, where the aggregate and idiosyncratic shocks are randomly drawn. In the counterfactual model, firms face a non-negative dividend constraint in each period, i.e. $e_t \geq 0$, so debt is their only source of external financing. The targeted moments are the same as in the baseline model: investment rate, leverage, profit to asset, default rate and its volatility. In the baseline model, we internally calibrate the equity issuance cost c_e to target the mean leverage, whereas in the counterfactual model, we interanlly calibrate the maximum recovery rate of bonds, $B^{\max}$.

Table A.4: Parameterization in GE Model

Parameter	**Description**	**Target**
Preferences and technology		
χ	Capital share	0.36
α	Returns to scale	0.85
δ	Depreciation rate	0.025
β	Time preference	0.99
γ	Risk aversion	1
μ_η	Idiosyncratic shock (mean)	0.52
σ_η	Idiosyncratic shock (volatility)	0.11
c_k	Investment adjust. cost	0.19
ρ_z	Profitability shock persistence	0.86
σ_ε	Profitability shock volatility	0.007
External financing		
τ	Corporate tax rate	0.3
ξ	Bankrupty cost	0.31
c	Coupon rate	0.0101
λ	Debt amortization rate	0.05
c_e	Equity issuance cost	0.203
$B^{\max}$	Maximum recovery rate	0.65
Learning		
σ_s	Volatility of signal	0.0091
σ_u	Volatility of noise	0.0057

Note: This table presents the calibrated parameters in the general equilibrium model (Section 6).

Table A.5: Parameterization in Model with Pessimistic Beliefs

Parameter	Description	Target
Preferences and technology		
α	Returns to scale	0.65
δ	Depreciation rate	0.025
β	Time preference	0.99
μ_η	Idiosyncratic shock (mean)	0.235
σ_η	Idiosyncratic shock (volatility)	0.186
c_k	Investment adjust. cost	0.10
ρ_z	Profitability shock persistence	0.83
σ_ε	Profitability shock volatility	0.0073
External financing		
τ	Corporate tax rate	0.3
ξ	Bankrupty cost	0.2
c	Coupon rate	0.0101
λ	Debt amortization rate	0.05
c_e	Equity issuance cost	0.112
$B^{\max}$	Maximum recovery rate	0.65
Learning		
σ_s	Volatility of signal	0.0091
σ_u	Volatility of noise	0.0054
ψ_p	Bias (pessimism)	−0.0138

Note: The model is calibrated to match moments for firms issuing high-yield bonds.

Table A.6: Parameterization in Model with Optimistic Beliefs

Parameter	Description	Target
Preferences and technology		
α	Returns to scale	0.65
δ	Depreciation rate	0.025
β	Time preference	0.99
μ_η	Idiosyncratic shock (mean)	0.124
σ_η	Idiosyncratic shock (volatility)	0.083
c_k	Investment adjust. cost	0.16
ρ_z	Profitability shock persistence	0.83
σ_ε	Profitability shock volatility	0.0073
External financing		
τ	Corporate tax rate	0.3
ξ	Bankrupty cost	0.2
c	Coupon rate	0.0101
λ	Debt amortization rate	0.05
c_e	Equity issuance cost	0.154
$B^{\max}$	Maximum recovery rate	0.65
Learning		
σ_s	Volatility of signal	0.0091
σ_u	Volatility of noise	0.0054
ψ_o	Bias (optimism)	0.0103

Note: The model is calibrated to match moments for firms issuing investment-grade bonds.

Table A.7: Moments with Alternative Learning Rules

	Data	**Baseline**	**Biased beliefs**		**Near rational**		**Overextrapolation**	
			Pessimism	Optimism	$\omega = 0.1$	$\omega = 0.3$	$\zeta = 0.10$	$\zeta = 0.15$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
First moments								
Default rate	0.013	0.016	0.035	0.0032	0.016	0.018	0.021	0.025
Bond spread	0.019	0.021	0.032	0.0049	0.024	0.027	0.029	0.032
Leverage	0.267	0.291	0.262	0.323	0.289	0.287	0.281	0.275
Investment	0.018	0.022	0.065	0.048	0.021	0.019	0.017	0.013
Second moments								
Corr(default, output)	−0.431	−0.163	−0.107	−0.076	−0.127	−0.105	−0.242	−0.267
Corr(spread, output)	−0.573	−0.259	−0.148	−0.093	−0.236	−0.194	−0.316	−0.340
Corr(invest, output)	0.574	0.890	0.803	0.822	0.848	0.836	0.921	0.934
σ(spread)	0.011	0.018	0.029	0.004	0.026	0.033	0.025	0.029
σ(invest)/σ(output)	3.458	2.394	2.462	2.230	2.573	2.691	2.594	2.602

Note: This table presents the aggregate moments in the alternative learning models with biased beliefs. The data moments are calculated from Compustat. The model-implied moments are based on 2,000 quarters of simulated data for 5,000 firms, where the aggregate and idiosyncratic shocks are randomly drawn. Columns (1) and (2) show the aggregate data moments and their model counterparts in the baseline model with rational learning. Columns (3) and (4) show the model predictions with "pessimistic" and "optimistic" investors, respectively. Columns (5) and (6) report the scenario with near rational investors, who make random mistakes 10% and 30% of the time, respectively. Columns (7) and (8) present the model predictions under overextrapolation, such that investors believe that the persistence of the firm's profit is 10% and 15% higher than the actual persistence, respectively. The models with pessimism and optimism are calibrated to match moments for speculative-grade and investment-grade firms, respectively (see Tables A.5 and A.6).

Table A.8: Additional Supporting Evidence

This table summarizes additional supporting evidence from regressions of changes in corporate bond spreads and investment in the crisis:

$$\Delta R_{it} = \alpha + \beta Crisis_t + \gamma Controls_{it} + u_{it}$$

$Crisis_t$ is an indicator that takes value of one between 2007Q4 and 2009Q2, the sample period is 2005-2010 and the firm-level controls are size and current profitability (ROA). We measure investor expectations of corporate profits, Rev_{it}, as the current revision in investors' expectations of next quarter corporate profits. The measure is contructed as the change between current and last period's investor expectations of next quarter corporate profits. Quarterly information on expectations at the firm level is from IBES. In Panel A, the dependent variable is the quarterly change in corporate bond spreads and we split the sample based on the mean of Rev_{it} (Columns 1-2) and on junk-rated bond status (Column 3). For the latter, we also consider a measure of reliance on public signal based on Chen and Jiang (2006), which is defined as the correlation between forecast errors and deviations from consensus forecast. Because a negative correlation is indicative of over-weighting of the public signal, we classify as *Most Reliant on Public Signal*$_{it}$ those firms that are below the mean of the measure (Column 4). In Panel B, the dependent variable is the quarterly change in capital expenditures and we split the sample based on the mean of Rev_{it} (Columns 1-2) and on junk-rated firm status (Columns 3) as well as on *Most Reliant on Public Signal*$_{it}$ (Column 4). t-statistics are based on standard errors that are clustered at the firm level to allow for within-firm serial correlation.

Panel A: Corporate Bond Spreads' Spike in the Crisis				
	Most Negative Rev_{it}		Junk Rated &	
	Yes	No	Most Negative Rev_{it}	Most Reliant on Public Signal$_{it}$
	[1]	[2]	[3]	[4]
β	0.607	0.414	1.230	1.257
[t]	[18.08]	[15.21]	[8.98]	[9.22]
Bond FE	Yes	Yes	Yes	Yes
Obs	23,560	32,019	3,637	3,913
Bonds	1,491	1,746	333	304
R^2	0.15	0.10	0.24	0.18

Panel B: Investment Contraction in the Crisis				
	Most Negative Rev_{it}		Most Negative Rev_{it}&	
	Yes	No	Junk Rated	Most Reliant on Public Signal$_{it}$
β	-0.618	-0.296	-0.661	-0.662
[t]	[-10.69]	[-6.31]	[-5.62]	[-8.71]
Firm FE	Yes	Yes	Yes	Yes
Obs	19,476	22,620	5,027	6,235
Firms	2,900	3,288	726	1,194
R^2	0.12	0.12	0.10	0.15