The Behavioral Financial Accelerator*

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Abstract

Risk premia in debt markets are wide, volatile, and forecast real macroeconomic outcomes. We develop a unified quantitative account of these facts based on information frictions in debt markets. Our key mechanism is that debt investors form beliefs about firms' creditworthiness by "following the herd" – i.e., using publicly-available information on quarter-ahead corporate profits from surveys of professional forecasters. Via this herding mechanism, biases in expectations transmit to debt prices and the macroeconomy. In a long time-series of quarterly U.S. data between 1970 and 2010, we find strong evidence in support of the mechanism. Short-term changes in expectations of corporate profits strongly forecast a variety of measures of expected risk premiums in the corporate bond market, as well as real economic aggregates such as GDP, investment, and employment growth over up to two years horizons. The mechanism is also quantitatively important, as a calibrated version of our model generates much wider and more volatile credit spreads than the rational expectations benchmark, and fits remarkably well the historically large spike in spreads during the financial crisis. Overall, our results suggest that informational inefficiencies are critical to understand large volatility episodes in debt markets and their consequences for the macroeconomy.

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1 Introduction

That investors in financial markets often behave following the wisdom of the crowd has long been known in financial economics going as far back as Keynes (1936), and is well-recognized in classic accounts of financial crises by Minsky (1977, 1986) and Kindleberger (1978). Yet this type of investor behavior have received surprisingly little consideration in the recent literature on credit cycles that has developed since the 2008-2009 global financial crisis. A number of important stylized facts are now established that are consistent with investor sentiment driving credit cycles, including the predictability of corporate bond returns (Greenwood and Hanson, 2013) and, in turn, of business cycle outcomes (Gilchrist and Zakrajšek, 2012 and López-Salido, Stein, and Zakrajšek, 2017). But the debate on whether credit-market sentiment drives recessions or is rather just a side-show of investment opportunities that vary over the business cycle remains open (for an example of the latter view, see Gomes, Grotteria, and Wachter, 2019).

This paper shows how credit cycles can originate from credit-market investors "following the herd". Specifically, we build a model in which debt investors form beliefs about firms' creditworthiness using publicly-available information on quarter-ahead corporate profits from surveys of professional forecasters. We show that this simple behaviorally plausible mechanism generates realistic credit cycles that are not just a side-show of the macroeconomy. A new stylized fact that is unique to our mechanism is that short-term changes in professional forecasts of corporate profits are a strong predictor of credit spreads and macroeconomic aggregates at long horizons. Another key fact that we can account for is the negative co-movement between credit spreads and macro aggregates, which is in sharp contrast to the counterfactual prediction of positive co-movement based on rational expectations. In all, our analysis shows that informational inefficiencies help to understand critical features of credit cycles that are otherwise puzzling from the standpoint of efficient debt markets under rational expectations.

The mechanism at the core of our model of credit cycles is testable and our first contribution is to document strong supporting evidence for it. 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 and macroeconomic aggregates 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 U.S. and is closely watched by market participants. Changes in the SPF consensus forecast of next quarter profits are strongly negatively correlated 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). Changes in short-term expectations forecast excess bond returns over up to 2 years horizons.

In the empirical analysis, we also show that in turn, by inducing time-variation in expected returns to credit market investors, short-term changes in expectations are an important driver of aggregate fluctuations on the real side of the economy. Between 1970 and 2010, our survey-based measure of short-term changes in investor expectations of corporate profits has significant forecasting power for various standard economic aggregates, including GDP growth, and business investment and employment growth over up to 2 years horizons. 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 motivates our modeling choices for credit-market investors' beliefs.

Next, we build a tractable quantitative model of firm financing and investment to show that the economic mechanism at the core of our theory of credit cycles is quantitatively important. We introduce learning by uninformed debt-market investors into an otherwise standard dynamic corporate finance setup (Kuehn and Schmid, 2014, Gomes and Schmid, 2017). 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' beliefs about firm creditworthiness affect debt pricing and, thus, firm leverage and investment decisions; second, credit-market investors are uninformed about the creditworthiness of the firm and form beliefs about it by "following the herd" – i.e., using publicly-available information on quarter-ahead corporate profits from surveys of professional forecasters. These two stark ingredients have powerful implications. A deterioration in short-term expectations of corporate profits leads to a lasting widening of credit spreads. And, if short-term expectations are pro-cyclical, then credit spreads are counter-cyclical.

For a realistic parametrization that is calibrated to match average investment, leverage, profitability, and default rates, we show that the model can replicate the sign and magnitude of key stylized facts of the credit cycle more successfully than the rational expectations benchmark. In particular, the model generates the right negative co-movement between credit spreads and macroeconomic aggregates, as well as the right negative co-movement between default rates and macro aggregates. By contrast, both credit spreads and default rates are counterfactually pro-cyclical in the rational expectations benchmark. The model also boosts the volatility of investment relative to the rational expectations 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 rational expectations and is closely aligned with its empirical counterpart. Overall, our theory results show that "following the herd" behavior of credit-market investors is central to a successful analytic account of credit cycles.

Our paper makes three main contributions. First, recent research in finance and macroeconomics has examined the link between investor sentiment and credit cycles. Greenwood and Hanson (2013) show that periods of credit growth are associated with low future returns to credit investors, as well as bust periods when credit declines. Greenwood, Hanson, and Jin (2019) develop a model of the endogenous two-way feedback between credit market sentiment and credit market outcomes. López-Salido, Stein, and Zakrajšek (2017) show that fluctuations in credit market sentiment are closely tied to future movements in aggregate economic activity. While these papers show convincing theory and evidence that credit market sentiment matters, the ultimate sources of sentiment are relatively understudied. Our contribution is to highlight the role of learning by credit-market investors as a source of sentiment, and to develop a quantitative theory of sentiment.

Second, we contribute to the vast literature on investment-based asset pricing (e.g., Chen, 2010, Gomes and Schmid, 2017, Gomes, Yaron, and Zhang, 2003) by showing that credit-market investors' learning constitutes a useful ingredient to improve the business cycle performance of this class of models. Third, we contribute a quantitative model to the classical literature on learning and herding in finance. Theory contributions include Scharfstein and Stein (1990), Froot, Scharfstein, and Stein (1992), and 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 Fang, Song, Dan, and Yi (2019) shows that herding and correlated trading are especially pronounced among credit market investors and have price impact.

The paper is structured as follows. Section 2 discusses how we measure investor expectations and summarizes the stylized facts. Section 3 presents a firm financing model with endogenous default and incomplete information in debt markets. Section 4 illustrates our main mechanism in a simple two-period setting. Section 5 describes our parametrization strategy. Section 6 discusses the quantitative implications of informational frictions on debt prices and corporate investment. Section 7 deviates from rational expectations, and considers near-rational learning and behavioral biases.

2 Empirical Evidence

Our empirical analysis has two parts. First, we show that there is a strong relation in the time-series between changes in investor expectations of corporate profits and excess returns to corporate bond holders. Second, we show that in turn, by inducing time-variation in expected returns to credit market investors, changes in expectations are an important driver of aggregate fluctuations on the real side of the economy.

Measure of Investor Expectations 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:

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

i.e. it is as the change between current and last period's investor expectations of next quarter corporate profits. The second explanatory variable of interest measures the noise in investor expectations of corporate profits, σ_t, defined as 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 In the first part of the analysis, we show that changes in investor expectations are strongly negatively correlated with a variety of measures of expected risk premiums in the corporate bond market. We do so in both univariate and multivariate time-series of forecasting regressions of excess bond returns on investor expectations of corporate profits.

Table 2 presents the baseline results of univariate forecasting regressions:

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

where $R_{t\to t+k}$ 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 noise σ_t – in each quarter. For robustness, we consider three measures of expected risk premiums in the corporate bond market, which include the excess return on corporate bonds (Panel A), 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). 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.

In addition, we repeat the exercise by adding control variables to the baseline regressions:

$$R_{t\to t+k} = \alpha + \beta X_t + \gamma Controls_t + u_{t+k}, \tag{2}$$

where $Controls_t$ 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. The results are presented in Table 3.

Since the measures of expectations are scaled by their respective unconditional standard deviation, we can interpret the coefficients in Tables 2 and 3 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. In all, we find that changes in expectations forecast excess bond returns over up to 2 years horizons, and investor expectations of corporate profits are an important force driving time-variation in expected returns to credit market investors.

Expectations of Corporate Profits and the Business Cycle In the second part of the empirical analysis, we show that our survey-based measure of changes in investor expectations of corporate profits has significant forecasting power for various standard economic aggregates, including GDP growth, and business investment, consumption and employment growth (Tables 4 and 5). We do so in 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:

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

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 (equation 2) using either our measure of expectations of corporate profits Rev_t or its noise 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. As such, our evidence on the real side 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.

3 A Firm Financing Model with Information Frictions

In this section, we build a firm financing model with endogenous default and incomplete information. The firm can finance investment either internally through accumulated earnings or externally through debt and equity. In line with the existing literature (see, for example, Hennessy and Whited (2007); Gomes and Schmid (2017)), we assume the standard trade-off between debt and equity finance: on the one hand, equity financing entails issuance costs; on the other hand, debt financing is costly because repayment is not enforceable and default entails deadweight loss. Thus the price of debt adjusts to reflect the probability of default.

Departing from the standard asset pricing with default risk literature, we consider information frictions in debt markets. In particular, we assume that the bond investors know the structure of the economy but cannot directly observe a firm's financial health or its default probability. Instead, investors must learn about the latent state of the firm from some publicly available signals. In what follows, we provide a model framework to study how rational learning about a firm's latent features affects corporate bond pricing.[1]

3.1 Technology and Income Processes

Assume that a firm produces output y_t using decreasing returns to scale technology

$$y_t = A_t k_t^{\alpha}, \text{ with } \alpha < 1,$$

where k_t is the capital input, and A_t is aggregate productivity that follows an AR(1) process in logs:

$$\log A_t = \rho_a \log A_{t-1} + \varepsilon_t^a \tag{3}$$

[1]In seeking to explain business cycle fluctuations with changes in expectations, this paper is related to, for example, Eusepi and Preston (2011); Lorenzoni (2009); and Jaimovich and Rebelo (2009). Moreover, both Adam, Marcet, and Beutel (2017) and this paper use survey measures of expectations to study fluctuations in asset prices. While Adam, Marcet, and Beutel (2017) focus on the boom-bust cycle in the stock markets, we focus here on the debt markets, and the implications of bond price fluctuations on the real economy.

and $\varepsilon_t^a \sim N(0,\sigma_a^2)$. After production, the firm receive a shock (proportional to capital) to their operating profit $z_t k_t$, and z_t follows an AR(1) process:

$$z_t = \mu_z + \rho_z z_{t-1} + \varepsilon_t^z \tag{4}$$

where μ_z is the mean cost of operation, and $\varepsilon_t^z \sim N(0,\sigma_\varepsilon^2)$. ε_t^z and ε_t^a are independent. Thus, the firm's operating profit in period t (before tax) is:

$$\Pi_t = A_t k_t^\alpha - z_t$$

Capital accumulation follows:

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

subject to a quadratic investment adjustment cost:

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

3.2 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 infinite maturity. In every period, it pays back a fraction λ of the principal, while the remaining $(1-\lambda)$ remains outstanding, which implies that the bond issued 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, so the total required amount of repayment in each period sums to $\big(c+\lambda\big)b_t$, where b_t is the stock of outstanding debt. With limited liability, the equity value of the firm is bounded below at zero.

A firm can also issue equity $e_t < 0$, which entails an issuance cost that captures the underwriting fees and costs to overcome any asymmetric information problem. As in Gomes and Schmid (2017), we adopt a reduced-form approach here by choosing a proportional equity issuance cost:

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

where $1_{e_t<0}$ is an indicator variable that equals to 1 if $e_t < 0$, and 0 otherwise.

3.3 The Firm's Problem

In each period, the equity holders can default on its debt obligation if the equity value of the firm $J(b_{t+1}, k_{t+1}, z_{t+1}, A_{t+1})$ falls below zero. This pins down a cutoff level z^*_{t+1} and ε^{z*}_{t+1} that satisfy:

$$J(k_{t+1}, b_{t+1}, z^*_{t+1}, A_{t+1}) = 0 \tag{6}$$

$$\varepsilon^{z*}_{t+1}(z_t, b_{t+1}, k_{t+1}, A_{t+1}) = z^*_{t+1} - \mu_z - \rho_z z_t \tag{7}$$

such that the firm repays in period $t+1$ if $\varepsilon_{t+1} \leq \varepsilon^{z*}_{t+1}(z_t, b_{t+1}, k_{t+1}, A_{t+1})$, and defaults otherwise.

We define the equity value $J(\cdot)$ in two parts (e.g. Gomes, Jermann, and Schmid, 2016):

$$J(k_t, b_t, z_t, A_t) = \max\left[0,\ \underbrace{(1-\tau)\big(A_t k_t^{\alpha} - z_t\big)}_{\text{after-tax profit}} - \underbrace{(c+\lambda)b_t}_{\text{debt payment}} + \underbrace{\tau\big(\delta k_t + c b_t\big)}_{\text{tax rebate}} + V(k_t, b_t, z_t, A_t)\right] \tag{8}$$

where $V(\cdot)$ is the firm's continuation value, which summarizes the effect of investment and financing decisions on the equity value:

$$\begin{aligned} V(k_t, b_t, z_t, A_t) = \max_{b_{t+1}, k_{t+1}, e_t} \Bigg\{ & q_t\Big(b_{t+1} - (1-\lambda)b_t\Big) - \Big(k_{t+1} - (1-\delta)k_t\Big) - g(k_t, k_{t+1}) \\ & + \Lambda(e_t) + \beta \mathrm{E}_t\left[\int_{-\infty}^{\varepsilon^{z*}_{t+1}} J\big(k_{t+1}, b_{t+1}, z_{t+1}, A_{t+1}\big) dF(z_{t+1})\right]\Bigg\}, \end{aligned} \tag{9}$$

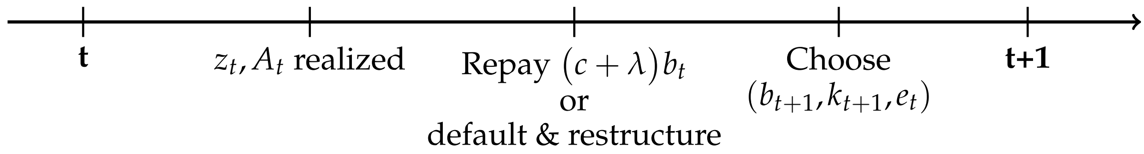

Figure 1: Timing of Firms' Problem

subject to (5), (7), and the definition of equity payout / issuance:

$$e_t = (1-\tau)\big(A_t k_t^{\alpha} - z_t\big) - \big(c+\lambda\big)b_t - \big(k_{t+1} - (1-\delta)k_t\big) - g\big(k_t, k_{t+1}\big)$$
$$+\tau\big(\delta k_t + c b_t\big) + q_t\Big(b_{t+1} - (1-\lambda)b_t\Big).$$

We use q_t to denote the market price of one unit of debt during period t, b_t is the stock of outstanding defaultable debt, so $q_t\big(b_{t+1} - (1-\delta)b_t\big)$ is the market value of new debt issues during period t.

The timing of the firm's problem is shown in Figure 1. At the beginning of each period, the firm carries debt b_t and capital k_t for current period's production. Upon observing the shocks A_t and z_t, profit Π_t is realized, and the firm faces the decision 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; otherwise, the shareholders walk away from the firm, and investors take over and restructure it. After restructuring, the investors sell off the equity portion to new owners, who then choose b_{t+1}, k_{t+1}, and e_t. We now turn to the bond investors' problem.

3.4 Bond Investors' Problem

Investors can buy corporate debt at price q_t, and collect coupon and principal payments 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 the default states, the investors' payoff consists of the firm's current after-tax profit $(1-\tau)\Pi_{t+1}$, the total enterprise value $V\big(\cdot\big)$, and the market value of remaining debt $(1-\lambda)q_{t+1}b_{t+1}$, net of the deadweight loss ξk_{t+1}, with $\xi \in (0,1]$. We cap the recuperation rate of the bond, $\tilde{B}_{t+1}$ at 80 percent. Otherwise as the firm grows larger, debt would never be risky regardless of their leverage (e.g. Begenau and Salomao, 2019).

Perfect Information If investors can observe z_t, then they can compute the default threshold ε^*_{t+1} directly using (7), as well as the recuperation rate of the bond:

$$\tilde{B}_{t+1}(b_{t+1},k_{t+1},z_{t+1},A_{t+1}) = \min\Bigg[\max\Big[0, \Big((1-\tau)\big(A_{t+1}k^{\alpha}_{t+1} - z_{t+1}\big) + V(k_{t+1},b_{t+1},z_{t+1},A_{t+1}) \\ +(1-\lambda)q_{t+1}b_{t+1} - \xi k_{t+1}\Big)\frac{1}{b_{t+1}}\Big],\ 0.8\Bigg].$$

As a result, the price of bond b_{t+1} raised in t follows the standard no-arbitrage condition:

$$q_t(b_{t+1},k_{t+1},z_t,A_t) = \beta \mathrm{E}_t\left\{F\big(\varepsilon^*_{t+1}\big)\Big[c+\lambda+(1-\lambda)q_{t+1}\Big] + \int_{\varepsilon^{z*}_{t+1}}^{+\infty} \tilde{B}_{t+1}(b_{t+1},k_{t+1},z_{t+1},A_{t+1})dF(\varepsilon_{t+1})\right\}. \tag{10}$$

Imperfect Information with Rational Learning Now suppose that investors observe the evolution of aggregate productivity A_t, the firm's decision rules (b_{t+1},k_{t+1}), and they know the structure of the economy – including the law of motion for z_t (4). However, they cannot observe the cash-flow shock to the firm's profit z_t, even after its realization. Consequently, they do not know the firm's true financial soundness Π_t, and cannot compute the true default threshold ε^{z*}_{t+1}, or their payoff if default occurs $(\tilde{B}_{t+1})$.

Nonetheless, investors can observe a signal s_t about the current period's shock to the firm's cash-flow ε_t. Then investors can form estimates of z_t and Π_t using the following system of equations:

$$\Pi_t = A_t k^{\alpha}_t - z_t \tag{11}$$

$$z_t = \mu_z + \rho_z z_{t-1} + \varepsilon_t \tag{12}$$

$$s_t = \rho_s s_{t-1} - \varepsilon_t + u_t \tag{13}$$

where the last equation denotes the evolution of the signal. $u_t \sim N\big(0,\sigma^2_u\big)$ is an error

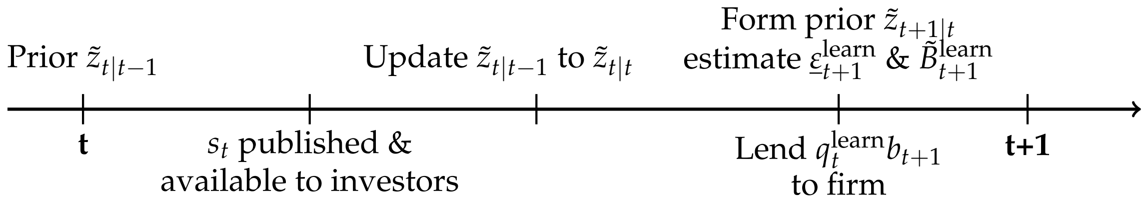

Figure 2: Timing of Investors' Learning Process

in the signal that is independent of ε^a_t and ε^z_t. As an empirical proxy for s_t, we use the current revision in investors' expectation of next period's corporate profit – as defined in (1) – normalized by the current GDP. Figure 3 plots the series from the Survey of Professional Forecasters between 1970Q1 and 2010Q4.[2] For this empirical proxy, the signal s_t is negatively related to the latent variable ε_t, since a positive shock to the firm's operating cost lowers today's profit Π_t as well as today's expectation of next quarter's profit $\mathrm{E}_t[\Pi_{t+1}]$.

The timing of investors' problem is summarized in Figure 2. After observing s_t, the investors can use (12) and (13) to form an estimate of z_t, given the history of observed data up to period t, denoted by $\mathcal{S}_t = \{s_0, s_1, ..., s_t\}$:

$$\tilde{z} = \mathrm{E}\left[z|\mathcal{S}\right] = \frac{\mu_z}{1-\rho_z} - \frac{\sigma^2_\varepsilon}{\sigma^2_\varepsilon + \sigma^2_u} \sum_{j=0}^{\infty} \rho^j_z \left(s_{-j} - \rho_s s_{-j-1} - \bar{s}\right), \tag{14}$$

since u_t and ε_t are assumed to be independent and normally distributed. Then investors can form a prior estimate of z_{t+1}, given by:

$$\tilde{z}_{t+1|t} = \rho_z \tilde{z}_{t|t} \tag{15}$$

and use $\tilde{z}_{t|t}$, $\tilde{z}_{t+1|t}$, and (7) to estimate the next period's default threshold $\varepsilon^{*\text{learn}}_{t+1}$ and their payoff if the firm's default $\tilde{B}^{*\text{learn}}_{t+1}$:

$$\varepsilon^{*\text{learn}}_{t+1}(\tilde{z}_{t|t}, b_{t+1}, k_{t+1}) = z^*_{t+1} - \rho_z \tilde{z}_{t|t} \tag{16}$$

[2]The Kolmogorov-Smirnov test cannot reject the null that the empirical proxy is normally distributed (see Figure 4).

$$\tilde{B}^{\text{learn}}_{t+1}(b_{t+1},k_{t+1},\tilde{z}_{t+1|t},A_{t+1}) = \min\Bigg[\max\Big[0,\ \Big((1-\tau)\big(A_{t+1}k^{\alpha}_{t+1} - \tilde{z}_{t+1|t}\big)$$

$$+ V(k_{t+1},b_{t+1},\tilde{z}_{t+1|t},A_{t+1}) + (1-\lambda)q_{t+1}b_{t+1} - \xi k_{t+1}\Big)\frac{1}{b_{t+1}}\Big],\ 0.8\Bigg]. \tag{17}$$

Note that z^*_{t+1} is defined by (6), as in the perfect information case, since investors can observe the firm's decision rules (b_{t+1},k_{t+1}). Then investors price the bond according to:

$$q^{\text{learn}}_t(b_{t+1},k_{t+1},A_t,\mathcal{S}_t) = \beta \mathrm{E}_t\Bigg\{F\big(\varepsilon^{*\text{learn}}_{t+1}\big)\Big[c+\lambda+(1-\lambda)q_{t+1}\Big]$$

$$+\int_{\varepsilon^{*\text{learn}}_{t+1}} \tilde{B}^{\text{learn}}_{t+1}(b_{t+1},k_{t+1},\tilde{z}_{t+1|t},A_{t+1})dF(\varepsilon_{t+1})\Bigg\}. \tag{18}$$

To summarize, the bond pricing formula here (18) differs from the perfect information case (10) in three ways. First, bond prices under perfect information are a function of the underlying state z_t, which is not the case with imperfect information. Second, their estimated default probability (determined by $\varepsilon^{*\text{learn}}_{t+1}$) may not coincide with the true default probability ($\varepsilon^{*\text{learn}}_{t+1}$). Third, their estimate of the recuperation value ($\tilde{B}^{\text{learn}}_{t+1}$) is computed using $\tilde{z}_{t+1|t}$, and may not be the true value $\tilde{B}_{t+1}$.

3.5 Recursive Competitive Equilibrium

A recursive competitive equilibrium in the learning economy consists of: (1) value of the firm $J(b_t,k_t,z_t,A_t)$, the continuation value $V(b_t,k_t,A_t)$; (2) policy functions $b_{t+1}(b_t,k_t,z_t,A_t)$, $k_{t+1}(b_t,k_t,z_t,A_t)$; (3) bond pricing schedule $q^{\text{learn}}_t(b_{t+1},k_{t+1},A_t,\mathcal{S}_t)$, such that, for all t:

1. $b_{t+1}(b_t,k_t,z_t,A_t)$, $k_{t+1}(b_t,k_t,z_t,A_t)$, $J(b_t,k_t,z_t,A_t)$, and $V(b_t,k_t,z_t,A_t)$ satisfy the firm's optimization problem (8) and (9), given the bond pricing schedule (18);

2. $q^{\text{learn}}_t(b_{t+1},k_{t+1},A_t,\mathcal{S}_t)$ satisfies the break-even condition (18) subject to (14)–(17), given the law of motion for the signal (13), and the history of observed data $\mathcal{S}_t = \{s_0,s_1,...,s_t\}$.

4 Mechanism

In this section, we present a simple two-period model to illustrate the learning mechanism. In particular, we highlight how public signals can affect the level and volatility of spreads on a risky bond, when investors are uncertain about a firm's default probability. Our focus here is on the impact of information frictions on the supply of bonds, so here we take a partial equilibrium approach and take the firm's demand for bonds as given.

Consider the pricing of a one-period risky corporate bond whose payoff is given by:

$$x_{t+1} = \begin{cases} 1 & \text{with probability } p_{t+1} \\ \frac{\tilde{B}}{b} & \text{with probability } 1 - p_{t+1} \end{cases}$$

We assume in this section that the default probability $1 - p_{t+1}$ and the recovery rate $\frac{\tilde{B}}{b}$ are exogenous (where $\tilde{B}$ is the assets seized in default, and b is the level of borrowing), with $\frac{\tilde{B}}{b} < 1$. Moreover, investors cannot observe p_{t+1}, but they know that p_{t+1} follows:

$$p_{t+1} = \bar{p} + \varepsilon_{t+1} \quad \text{with } \; \varepsilon_{t+1} \sim N(0, \sigma_\varepsilon^2)$$

where $\bar{p}$ is the mean repayment probability, which is public information, and ε_{t+1} is a shock to the next period's repayment probability unobserved by the investors. Instead, investors observe a signal s_t at time t about ε_{t+1} according to:

$$s_t = \varepsilon_{t+1} + u_t \quad \text{with } \; u_t \sim N(0, \sigma_u^2),$$

where u_t is the noise in the signal, and is independent of ε_t. After observing signal s_t, a risk-neutral investor can price the one-period bond according to:

$$\begin{aligned} q_t &= \beta \mathrm{E}_t \Big[p_{t+1} + \frac{\tilde{B}}{b}(1 - p_{t+1}) \Big| s_t \Big] \\ &= \beta \Big(\frac{\tilde{B}}{b} + \Big(1 - \frac{\tilde{B}}{b}\Big) \mathrm{E}_t \Big[p_{t+1} \Big| s_t \Big] \Big) \\ &= \beta \left(\frac{\tilde{B}}{b} + \Big(1 - \frac{\tilde{B}}{b}\Big) \left[\bar{p} + \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_u^2} s_t \right] \right). \end{aligned}$$

If the investors are risk-neutral, the spread between the risky bond and the risk-free bond is given by:[3]

$$
\begin{aligned}
\tilde{R}_{t+1} &= \mathrm{E}_t\left[1 - x_{t+1}\right] \\
&= \left(1 - \mathrm{E}_t\left[p_{t+1}\middle|s_t\right]\right)\left(1 - \frac{\tilde{B}}{b}\right) \\
&= \left(1 - \left[\bar{p} + \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_u^2} s_t\right]\right)\left(1 - \frac{\tilde{B}}{b}\right) \\
&= \underbrace{(1 - \bar{p})\left(1 - \frac{\tilde{B}}{b}\right)}_{\text{default premium}} - \underbrace{\frac{\sigma_\varepsilon^2\left(1 - \frac{\tilde{B}}{b}\right)}{\sigma_\varepsilon^2 + \sigma_u^2} s_t}_{\text{learning}}
\end{aligned} \tag{19}
$$

Therefore, under the risk neutral assumption, the level of spread is determined by two factors: the first term is the standard default premium, and the second term shows the extent to which the signal (s_t) about the firm's default probability affects the investors' pricing decision. In particular, equation (19) shows that, ceteris paribus:

1. the more positive the signal about the repayment probability (higher s_t), the lower the spread;

2. the "noisier" the signal (higher σ_u), the higher the spread.

We can infer from these findings that if the signal series is procyclical, then the spread is likely to be countercyclical, for a given level of demand. Moreover, if the signal is noisier during recessions, then the degree of countercyclicality is stronger.

These results summarize how using public signals can affect investors' pricing of debt qualitatively, when they are uncertain about the firm's default probability. We now explore the quantitative implications of such uncertainty through the lens of the firm financing model set up in section 3, where both the demand and supply of bonds are endogenously determined.

[3]Following Dow, Gorton, and Krishnamurthy (2005), we define the spread between the corporate and the riskless bonds as the ratio of two bond prices (as opposed to the difference in the reciprocals of the two prices) for analytical tractability.

5 Parameterization and Model Fit

Parameterization The model is calibrated at quarterly frequency between 1985Q1 and 2010Q4. There are 16 parameters in the benchmark model with rational learning:

$$\{\alpha, \delta, \beta, \tau, c, \lambda, \rho_a, \sigma_a, \rho_z, \sigma_\varepsilon, \rho_s, \sigma_u, \xi, \mu_z, c_e, c_k\}.$$

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. We set the next parameter, the periodic coupon rate, as $c = 1/\beta - 1$, so that the price of default-free debt is equal to 1.

The next seven parameters $\{\lambda, \rho_a, \sigma_a, \rho_z, \sigma_\varepsilon, \rho_s, \sigma_u\}$ are calibrated according to their natural data counterpart. We set λ equal to 0.05 per quarter, implying an average expected maturity of five years, similar to the value used in Gomes, Jermann, and Schmid (2016). We calibrate the aggregate productivity parameters $\{\rho_a, \sigma_a\}$ using quarterly U.S. GDP. To calibrate the persistence and volatility of the firm's operating cost $\{\rho_z, \sigma_\varepsilon\}$, we use the "cost of goods sold" item from Compustat, and fit an AR(1) after demeaning the series scaled by total assets. To calibrate the parameters governing the evolution of the signal, we first fit an AR(1) to our empirical proxy – the current revision in investor's expectation of next period's corporate profit (1) – to get an estimate for the persistence and the volatility of the signal $\{\rho_s, \sigma_s\}$. Given σ_s and σ_ε, we then use the following relation to identify σ_u:

$$\sigma_u^2 = \sigma_s^2 - \sigma_\varepsilon^2.$$

This relation comes from equation (13), under the maintained assumption that ε_t^z and u_t are independent and normally distributed.

The last four parameters $\{\xi, \mu_z, c_e, c_k\}$ are calibrated to target the mean default rate, mean profit-to-asset ratio, mean leverage ratio, and mean investment rate. Default rates are 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 (Moody's Investor Service, 2014). The moments on profitability, leverage and investment are constructed using data from Compustat for the sample period.

We discretize the productivity shock A_t and the shock to operating cost z_t using Tauchen (1986). Since the model is nonlinear, we solve it globally. For a given set of values for $\{\lambda, \mu_z, c_e, c_k\}$, we first solve for the policies of the firm by value function iterations, given a menu of bond prices $q_t^{\text{learn}}(b_{t+1}, k_{t+1}, A_t, \mathcal{S}_t)$. Then we compute the targeted moments by simulating data using the realized series of technology (A_t) and operating cost (z_t), the revision series (s_t), and the policies of the firm for the period 1985Q1-2010Q4. We then compare the model-implied moments from this set of parameters with the data moments, and repeat the second step until the difference between the two is minimized to find $\{\lambda, \mu_z, c_e, c_k\}$. The parameter values in the baseline model with rational learning are summarized in Table 7.

It is worth mentioning that in this quantitative exercise, we estimate the learning parameters using an expanding window: for each quarter, we estimate ρ_s and σ_u using all the data points from the revision series starting from 1971Q1 up to the current period. This captures the idea that investors can only use the history of observed data (up to the current period) $\mathcal{S}_t = \{s_0, s_1, ..., s_t\}$ to estimate the learning parameters. Table 8 reports the empirical estimates of ρ_s and σ_u during 1985Q1-2010Q4. For our quantitative analysis, we create bins for s_t, ρ_s and σ_u, in order to solve for the menu of bond prices $q_t^{\text{learn}}(b_{t+1}, k_{t+1}, A_t, \mathcal{S}_t)$.

Model Fit Table 9 presents the model predictions of the aggregate moments and their data counterparts. Panel A presents the targeted moments and the model response, whereas panel B shows the non-targeted moments for credit spreads, default rates, and investment. Comparing the data moments in column (1) with those in column (2), the learning model is able to capture the countercyclical default rates and credit spreads, and can generate a reasonable level of spread despite the low default rate associated with the long-term debt. Moreover, the model can generate countercyclical spreads without imposing time-varying default cost or introducing other types of aggregate shock. We argue that this arises due to informational inefficiencies, such that the investors form beliefs about firms' creditworthiness using publicly-available information. We explain this in further detail and illustrate the quantitative significance of information frictions in the next section.

6 Quantitative Results

6.1 Model-Implied Credit Spreads

We simulate the economy between 19850Q1 and 2010Q4, using the realized series of TFP (A_t), cost of operation (z_t), and the measure of expectations from survey data (s_t), to examine the model-implied credit spreads during the period. Figure 5 compares the data with the model-implied series from the imperfect information model with rational learning. In the same figure, we also plot the model-implied spreads in a counterfactual model with complete information. In this economy, the firm's problem is the same as in the learning economy, but the bond pricing schedule is given by $q_t(b_{t+1}, k_{t+1}, z_t, A_t)$ (see equation 10), instead of $q_t^{\text{learn}}(b_{t+1}, k_{t+1}, A_t, \mathcal{S}_t)$; in other words, the investors and the firm have the same information set in this economy. To facilitate comparison, we calibrate the counterfactual model under the same parameterization as outlined in Table 7, leaving out the learning parameters $\{\sigma_u, \rho_s, \sigma_s\}$.

The imperfect information model produces fluctuations in credit spreads that are more or less in line with the movements in the data, especially during the Great Recession. On the other hand, the counterfactual model with complete information does a poor job at matching the data. The complete information model predicts on average lower and less volatile spreads than the model with learning. Moreover, the volatilities of the predicted series in the complete information model are more or less constant over the sample period – i.e., the volatilities in the 1980s are of a similar degree to the volatilities in 2008 – which is not the case in the data. By contrast, the imperfect information model does a better job at distinguishing the "spikes" in the more recent recessions. One explanation for this is that the measured expectation (as shown in Figure 3) was more volatile in the 2000s than in the 1980s. By directly feeding in this series as well as estimating σ_u and ρ_s using an expanding window, we are able to better capture the price movements in the corporate debt markets over time.

6.2 Impact of Information Frictions on Credit Spreads

Table 10 compares the moments generated from the imperfect information model with those from the complete information model. We find that informational inefficiencies in the debt markets have two types of impact on credit spreads. First, bond spreads are higher and more volatile when investors cannot observe the latent state of the firm. Second, without information frictions, credit spreads are counterfactually procyclical in a technology-driven business cycle with costly external finance.

Credit Spread Puzzle As shown in Table 10, the average default rate and spread are significantly lower in the perfect information model than in the data. This echoes the "credit spread puzzle" – that the observed spreads on bonds are much larger than what can be explained by empirically plausible default rates.

Recall from section 4 that the higher level of spreads under imperfect information reflects the precautionary behavior by bond investors, which becomes stronger when the signal is more volatile. Since this mechanism is absent in the standard firm financing models with only financial frictions, the imperfect information model with learning does a better job at matching the mean level of credit spreads.

Besides the sample mean, the imperfect information model is significantly better at matching the movements in spreads during recessions – as shown in Figure 5 – assuming that productivity shock is the only source of aggregate fluctuations. The significant rise in credit spreads during crises could be driven by two interacting forces in the model: (i) bond spread is negatively related to the signal, which is countercyclical; (ii) bond spread is positively related to the volatility of the signal, which is procyclical.

Cyclicality of Credit Spreads It is well known that corporate bond spreads are strongly countercyclical in the data. However, earlier studies have shown that credit spreads tend to be counterfactually procyclical in technology-driven business cycle models with costly external finance (see, for example, Gomes, Yaron, and Zhang, 2003; Gilchrist, Sim, and Zakrajšek, 2014). This counterfactual prediction arises because an adverse technology shock reduces profitable investment opportunities, and therefore lowers a firm's incentive to borrow. A reduction in leverage, however, lowers the firm's default risk, which leads to a lower level of credit spread. In other words, an adverse technology shock induces an inward shift in the demand for credit, which makes quantities and prices move in the same direction, thereby generating procyclical credit spreads. We confirm this prediction in our counterfactual model: as shown in column (3) of Table 10, both spreads and default rates are procyclical in the perfect information model.

By contrast, the imperfect information model can generate countercyclical spreads, even under the assumption that TFP shocks are the only source of aggregate fluctuations.[4] This is because the measured expectations are highly countercyclical, and the spreads react negatively to them. Ceteris paribus, when investors receive an adverse signal about the firm during a recession, the supply of bonds shifts inward, so the quantity of borrowing and its cost move in opposite directions. Quantitatively, the inward shift in supply exceeds the shift in demand, because their expectations not only turn sour, but also become noisier during recessions.

6.3 Aggregate Implications of "Noisier" Signals

We perform three comparative static exercises to study the impact of noisy signals on both financial and real variables, and whether such impact depends on how leveraged the corporate sector is. In the first exercise, we double the noise level in the signal σ_u and re-simulate the model, keeping the rest of the parameters unchanged. Next, we double σ_u as well as the equity issuance cost parameter c_e. In the last exercise, we only double c_e and keep σ_u the same as the baseline model. Table 11 compares the aggregate moments in the baseline (low noise-low leverage) and the counterfactual models (high noise-low leverage, high noise-high leverage, low noise-high leverage).

Comparing the baseline and the first counterfactual exercise, we see that, ceteris paribus, having noisier signals leads to higher spreads and lower investment, and the standard deviations of both variables increase. Investment decreases as the firm borrows less when the cost of borrowing is higher. The impact on default risk is the result of two forces: the cost of borrowing and the level of indebtedness. Given the parameterization, the effect of a lower leverage dominates, and the average default rate is lower in the counterfactual model.

In the second counterfactual exercise, we find that noisier signals lead to a bigger increase in credit spreads when the firm is more leveraged. Unlike the first counterfactual exercise, the default rate is unambiguously higher. Now the firm switches from equity financing to bond financing in the face of higher equity issuance costs. Nonetheless, under the given calibration, the increase in debt financing is less than the reduction in equity financing in equilibrium, as the firm endogenizes the increase

[4] Other sources of aggregate fluctuations – including uncertainty and financial shocks – can potentially generate countercyclical spreads in this class of models (Gilchrist, Sim, and Zakrajšek (2014); Arellano, Bai, and Kehoe (2018)).

in borrowing costs. As a result, there is less external financing in total and aggregate investment is lower.

Comparing across Table 11, we see that higher leverage implies higher credit spreads ($0.033 - 0.023 = 0.01$), but the additional impact of having noisier signals is stronger ($0.047 - 0.033 = 0.014$). Similarly, the decline in investment due to noisier signals ($0.017 - 0.021 = -0.004$) is larger than the decline due to more expensive external financing alone ($0.021 - 0.023 = -0.002$). This exercise suggests that there is an important interaction effect between financial frictions and incomplete information: Noisier signals have a larger effect on credit spreads and real activity when the corporate sector is more leveraged.

7 Alternative Learning Rules

So far the framework we set up is consistent with rational expectations. In this section, we deviate from the rational learning benchmark, and consider two alternative learning rules. The first one is near-rational learning, in which the investors still update their beliefs about the hidden state using the Bayes' rule but occasionally make mistakes. We assume these mistakes to be random, so *on average*. Under the second alternative learning rule, agents may have biased beliefs toward either the "good" or the "bad" states, depending on whether they are optimistic or pessimistic agents.[5] We present the aggregate implications of these alternative learning rules in Table 12.

7.1 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.

Specifically, the timing of investors' problem is the same as the rational learning case (Figure 2). Once they observe the public signal s_t, they update their prior belief

[5] Alti and Tetlock (2013) also study the impact of biased beliefs on asset prices through the lens of a neoclassical investment model. This paper complements their study on equity returns as we focus on the debt markets.

about the firm's latent state $\tilde{z}_{t|t-1}$ to $\tilde{z}_{t|t}$ according to:

$$\tilde{z}^{\mathrm{NR}}_{t|t} = (1-\omega)\tilde{z}_{t|t} + \omega\eta_t, \tag{20}$$

where $\tilde{z}_{t|t}$ is from the rational learning model, as defined in (14), η_t is an i.i.d. error, and ω is a weighting parameter in $[0,1]$. Hence the learning rule (20) is a weighted average of the updating process under rational learning and a random error. Once the investors form the updated belief about the state in the current period, the belief about the state tomorrow is again formed according to (15). As the error term is in the updating process, its effect lasts for more than one period since the updated belief serves as the prior for the next period.

We solve the model under the new updating rule (20), under the same parameterization as the rational learning benchmark. In addition, we calibrate $\omega = 0.1$, such that agents update their beliefs correctly 90 percent of the time. We simulate the model for the same sample period and compute the aggregate moments reported in Table 12. Comparing columns (1) and (2), we see that the main difference between the two models lies in the second moments, especially the volatilities. This stems from the assumption that the mistakes are random, hence the investors do not make systematic mistakes. As they receive a random error η_t 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.

7.2 Biased Beliefs: Optimism and Pessimism

Systematic Bias Intuitively, pessimistic agents tend to think the economy is in a "bad" state, whereas optimistic agents tend to bias their beliefs toward the "good" states. In our context, we say that an investor is "pessimistic" (or optimistic) if they believe that the default probability of the firm in the next quarter is higher (lower) than the expected default probability computed by an investor who learns rationally. For tractability, we capture the notion of biased beliefs in a reduced-form fashion by assuming that once the investors observe the signal s_t, they update their prior belief about the firm's latent state $\tilde{z}_{t|t-1}$ to $\tilde{z}_{t|t}$ according to:

$$\tilde{z}_{t|t}^{\text{bias}} = \tilde{z}_{t|t} + \psi, \tag{21}$$

where ψ is a constant and $\tilde{z}_{t|t}$ is from the rational learning model defined in (14). Consequently, their estimate of the default threshold is given by:

$$\varepsilon_{t+1}^{*\text{bias}}(\tilde{z}_{t|t}, b_{t+1}, k_{t+1}) = z_{t+1}^{*} - \rho_z \tilde{z}_{t|t}^{\text{bias}} = z_{t+1}^{*} - \tilde{z}_{t|t} - \psi.$$

Therefore, ψ is positive for pessimistic agents such that in comparison to a rational investor, their estimates of the default thresholds are lower, and the estimates of the firm's default probabilities are higher. By a similar argument, ψ is negative if the agents are optimistic.

We solve the model under the new updating rule (20) separately for the different directions of bias. For qualitative illustration, we calibrate ψ such that the pessimistic (optimistic) investors' estimates of the firm's default probability are, on average, 10 percent higher (lower) than the estimates by rational investors. Columns (3) and (4) of Table 12 present the aggregate moments when investors have biased beliefs, and the direction of bias is constant throughout the sample period. Contrary to the near-rational learning model, biased beliefs have more impact on the first moments than the second moments: With optimistic investors, the mean bond spread is lower, as one would expect, and this leads to higher leverage and investment over the sample period. The opposite is true when investors are systematically pessimistic. Moreover, unlike the near-rational learning model, the models with systematic biased beliefs predict less volatile aggregate variables (both real and financial) than the rational learning case. This holds for both optimistic and pessimistic beliefs. Intuitively, if investors are systematically optimistic (which is the case here since ψ is a constant), not only would they attach a higher probability to the non-defaulting ("good") state in a particular period, but they also perceive more periods to be in the "good" states. With less variability in their estimates of the firm's default probability, there is also less fluctuation in the credit spreads.

Cyclical Bias Next we examine the aggregate implications when the bias in investors' beliefs are procyclical, such that investors are more optimistic in boom times, and pessimistic in recessions. We simulate the economy under this assumption, by setting ψ to be positive during the NBER recessions, and negative otherwise. As before, we calibrate the two values $(\psi_{\text{boom}}, \psi_{\text{crisis}})$ such that the estimates of the firm's default probabilities are on average 10 percent lower than the estimates by a rational investor in booms, and 10 percent higher in recessions. The last column of Table 12 reports the aggregate moments in this model. With time-varying sentiments, we find that the volatilities of spread and investment are unambiguously higher, and credit spreads also become more countercyclical.

It is hard to interpret the first moments in column (5), since optimism and pessimism would affect the first moments in opposite directions, as shown in columns (3) and (4). Instead, it is more meaningful to examine the model-implied time path of spreads. While Figure 5 shows that when TFP is the only aggregate shock, the imperfect information model is significantly better at matching the cyclicality of spreads than the perfect information model, the imperfect information model under rational learning still appears to fall short at matching the level of spreads during the 2008-09 crisis. With a modest amount of cyclical behavioral bias, we illustrate in Figure 6 that the model can match the majority of the increase in spreads during the 2008 crisis.

8 Conclusion

In order to better understand the consequences of "following the herd" behavior by credit-market investors, we have combined time-series data on professional forecasts of corporate profits, bond returns, and macroeconomic outcomes with a novel behavioral model of credit cycles. Consistent with the idea that debt investors form beliefs about firms' creditworthiness using publicly-available information on short-term corporate profits from surveys of professional forecasters, we have documented that changes in quarter-ahead professional forecasts of corporate profits have strong predictive power for credit spreads and macroeconomic outcomes over long horizons. 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 expectations benchmark. As such, our model provides a plausible basis for informational inefficiencies in credit markets to transmit to the real economy.

There are several venues along which our approach can be extended. First, motivated by the strong evidence of predictability in debt markets of Greenwood and Hanson (2013), we have focused on informational inefficiencies in debt markets. While predictability is relatively weaker in equity markets and so is herding, it would be interesting to add informational inefficiencies 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 herding behavior in credit markets, including, for example, relative-performance evaluation type features in institutional investors' compensation contracts (Feroli, Kashyap, Schoenholtz, and Shin, 2014) or the concave relation between fixed-income fund flows and performance (Goldstein, Jiang, and Ng, 2017).

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 herding is a central idea in modern financial economics.

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Tables and Figures

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

This table presents summary statistics (annual means) for the two main explanatory variables over our sample period from 1971-2010 (Panel A) and for 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 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.

Panel A: Expectations of Corporate Profits					
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
			Std Dev	1.00	1.00
			N	151	151

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

Table 2: Expectations of Corporate Profits and Credit Spreads

This table summarizes results of univariate time-series forecasting regressions of excess bond returns on investor expectations of corporate profits:

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

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 BAA-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	-0.246	-0.230	-0.227	-0.215	-0.152	0.627	0.628	0.629	0.641	0.718
[t]	[-1.67]	[-1.72]	[-1.66]	[-1.72]	[-1.38]	[4.89]	[3.98]	[3.96]	[4.04]	[5.90]
R^2	0.06	0.05	0.05	0.04	0.02	0.38	0.39	0.41	0.44	0.51
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	-0.110	-0.096	-0.099	-0.094	-0.068	0.071	0.070	0.070	0.077	0.085
[t]	[-2.32]	[-2.15]	[-2.38]	[-2.61]	[-3.20]	[1.42]	[1.15]	[1.06]	[1.13]	[1.21]
R^2	0.06	0.04	0.05	0.05	0.03	0.02	0.02	0.02	0.03	0.04
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	-0.163	-0.143	-0.125	-0.109	-0.078	0.054	0.053	0.056	0.061	0.077
[t]	[-3.73]	[-3.55]	[-3.70]	[-3.71]	[-3.32]	[0.85]	[0.70]	[0.69]	[0.71]	[0.87]
R^2	0.13	0.11	0.09	0.07	0.05	0.01	0.01	0.02	0.02	0.04

Table 3: 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 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 4: 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 Panel B, $\widehat{R}_{t\to t+k}$ is the predicted 4- or 8-quarter cumulative excess return on BAA-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			
	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 5: Additional Business Cycle Outcomes

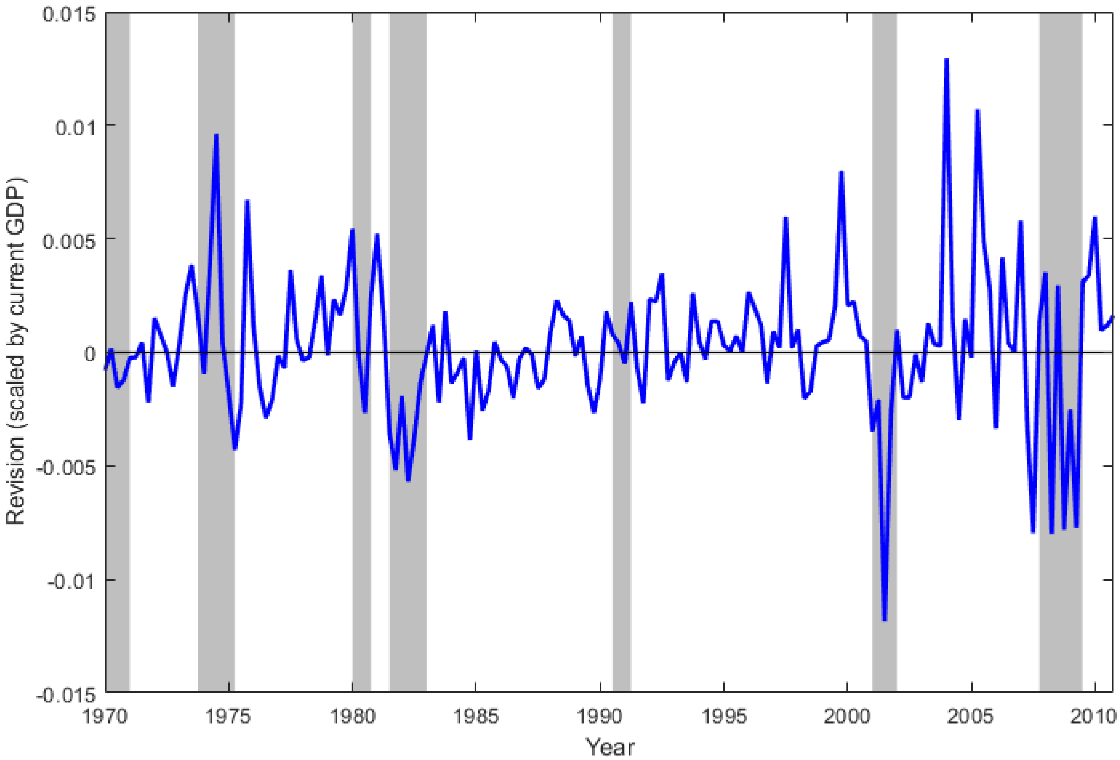
This table summarizes results of multivariate time-series forecasting regressions of business cycle aggregates on the component of excess bond returns that is predictable based on investor expectations of corporate profits, controlling for macroeconomic conditions (aggregate consumption, business investment, 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 Panel B, $\widehat{R}_{t\to t+k}$ is the predicted 4- or 8-quarter cumulative excess return on BAA-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.

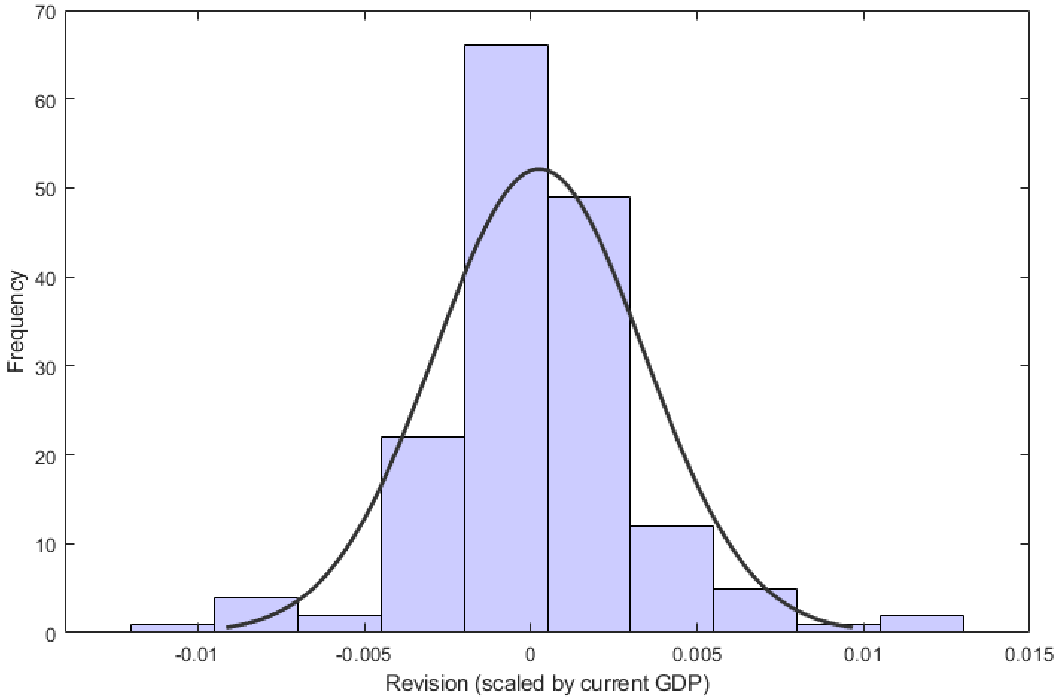
Panel A: Excess Return on Corporate Bonds								
	Rev_t				σ_t			
	Emp 4-qtr	Emp 8-qtr	Cons 4-qtr	Cons 8-qtr	Emp 4-qtr	Emp 8-qtr	Cons 4-qtr	Cons 8-qtr
β	-0.319	-0.329	0.132	-0.067	-0.551	-0.437	-0.235	-0.194
[t]	[-1.56]	[-3.08]	[0.031]	[-0.35]	[-8.00]	[-10.90]	[-3.10]	[-3.58]
R^2	0.71	0.75	0.36	0.40	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

Figure 3: 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, normalized by US GDP. Data is from the Survey of Professional Forecasters, and "revision" is defined as today's nowcast of profit levels minus last period's profit levels for the current quarter. Shaded areas indicate the NBER recession dates.

Figure 4: 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 (normalized by US GDP) – between 1970Q1 and 2010Q4. Data is from the Survey of Professional Forecasters, and "revision" is defined as today's nowcast of profit levels minus last period's profit levels for the current quarter. The Kolmogorov-Smirnov test statistic for the sample is 0.084 with a p-value of 0.184.

Table 7: Parameterization

Parameter	**Description**	**Target**
Preferences and technology		
$\alpha = 0.65$	Returns to scale	Hennessy and Whited (2007)
$\delta = 0.025$	Depreciation rate	NIPA depreciation
$\beta = 0.99$	Time preference	Annual risk-free rate 4%
$c_k = 0.824$	Adjustment cost	Mean investment rate
$\mu_z = 0.113$	Mean cash flow	Mean profit-to-asset
$\rho_z = 0.966$	Cash flow persist.	Cost of goods sold
$\sigma_\varepsilon = 0.0293$	Cash flow vol.	Cost of goods sold
$\rho_a = 0.97$	Agg. productivity persist.	US quarterly GDP
$\sigma_a = 0.007$	Agg. productivity vol.	US quarterly GDP
External financing		
$\tau = 0.3$	Corporate tax rate	Graham (2007)
$\xi = 0.26$	Bankrupty cost	Mean default rate
$c = 0.0101$	Coupon rate	Price of default-free debt
$\lambda = 0.05$	Debt amortization rate	Average debt maturity
$c_e = 0.157$	Equity issuance cost	Mean leverage ratio
σ_s (see Table 8)	Volatility of signal	Current rev. in expected profit
$\sigma_u = (\sigma_s - \sigma_\varepsilon)^{0.5}$	Volatility of noise in signal	Current rev. in expected profit

Note: This table presents the calibrated parameters in the baseline model with rational learning. The targeted moments and their data counterparts are reported in Table 9.

Table 8: Persistence (ρ_s) and Volatility (σ_s) of the Current Revision in Investors' Expectation of Next Quarter Corporate Profits (1985Q1-2010Q4)

Year	Quarter	ρ_s	σ_s	Year	Quarter	ρ_s	σ_s
1985	1	0.349	0.274	1998	1	0.310	0.231
1985	2	0.349	0.274	1998	2	0.306	0.231
1985	3	0.354	0.273	1998	3	0.311	0.231
1985	4	0.350	0.271	1998	4	0.309	0.230
1986	1	0.350	0.269	1999	1	0.309	0.229
1986	2	0.351	0.267	1999	2	0.309	0.228
1986	3	0.353	0.266	1999	3	0.310	0.228
1986	4	0.351	0.264	1999	4	0.331	0.237
1987	1	0.351	0.262	2000	1	0.322	0.237
1987	2	0.351	0.261	2000	2	0.326	0.236
1987	3	0.352	0.259	2000	3	0.325	0.236
1987	4	0.354	0.258	2000	4	0.325	0.235
1988	1	0.351	0.257	2001	1	0.324	0.236
1988	2	0.354	0.256	2001	2	0.331	0.236
1988	3	0.358	0.255	2001	3	0.368	0.258
1988	4	0.360	0.254	2001	4	0.346	0.258
1989	1	0.358	0.253	2002	1	0.340	0.257
1989	2	0.358	0.251	2002	2	0.338	0.257
1989	3	0.356	0.250	2002	3	0.341	0.257
1989	4	0.362	0.250	2002	4	0.340	0.256
1990	1	0.363	0.249	2003	1	0.340	0.255
1990	2	0.358	0.248	2003	2	0.338	0.254
1990	3	0.359	0.247	2003	3	0.337	0.253
1990	4	0.359	0.246	2003	4	0.338	0.252
1991	1	0.358	0.244	2004	1	0.340	0.274
1991	2	0.356	0.244	2004	2	0.301	0.273
1991	3	0.349	0.243	2004	3	0.297	0.273
1991	4	0.352	0.243	2004	4	0.290	0.273
1992	1	0.339	0.243	2005	1	0.289	0.272
1992	2	0.345	0.242	2005	2	0.285	0.284
1992	3	0.355	0.244	2005	3	0.299	0.286
1992	4	0.340	0.243	2005	4	0.303	0.286
1993	1	0.340	0.241	2006	1	0.294	0.286
1993	2	0.340	0.240	2006	2	0.279	0.287
1993	3	0.340	0.239	2006	3	0.276	0.286
1993	4	0.332	0.240	2006	4	0.276	0.285
1994	1	0.331	0.238	2007	1	0.275	0.288
1994	2	0.330	0.237	2007	2	0.254	0.288
1994	3	0.329	0.236	2007	3	0.273	0.295
1994	4	0.331	0.236	2007	4	0.252	0.294
1995	1	0.330	0.234	2008	1	0.255	0.294
1995	2	0.330	0.233	2008	2	0.233	0.300
1995	3	0.330	0.232	2008	3	0.206	0.300
1995	4	0.330	0.231	2008	4	0.190	0.306
1996	1	0.329	0.231	2009	1	0.196	0.306
1996	2	0.333	0.231	2009	2	0.210	0.311
1996	3	0.335	0.230	2009	3	0.187	0.311
1996	4	0.331	0.230	2009	4	0.191	0.311
1997	1	0.328	0.229	2010	1	0.202	0.313
1997	2	0.328	0.228	2010	2	0.200	0.313
1997	3	0.328	0.233	2010	3	0.201	0.312
1997	4	0.310	0.232	2010	4	0.201	0.311

Note: This table reports the empirical estimates of ρ_s in the AR(1) process: $s_t = \rho_s s_{t-1} + u_t$, where $u_t \sim N(0, \sigma_u^2)$, and the sample standard deviation of the signal (σ_s). For each quarter t, each estimate is computed using all the data points (from 1970Q1) up to the current period.

Table 9: Model Fit

Panel A: Targeted moments	Data (1)	Model (2)
Investment rate (mean)	0.018	0.023
Leverage (mean)	0.267	0.305
Profit to asset (mean)	0.053	0.069
Default risk (mean)	0.013	0.010

Panel B: Untargeted moments	Data (1)	Model (2)
Bond spread (mean)	0.019	0.017
Bond spread (std dev rel to output)	2.10	2.41
Corr(spread, output)	−0.57	−0.31
Default risk (std dev)	0.012	0.007
Corr(default, output)	−0.43	−0.17
Investment (std dev rel to output)	3.46	2.75
Corr(invest, output)	0.57	0.74

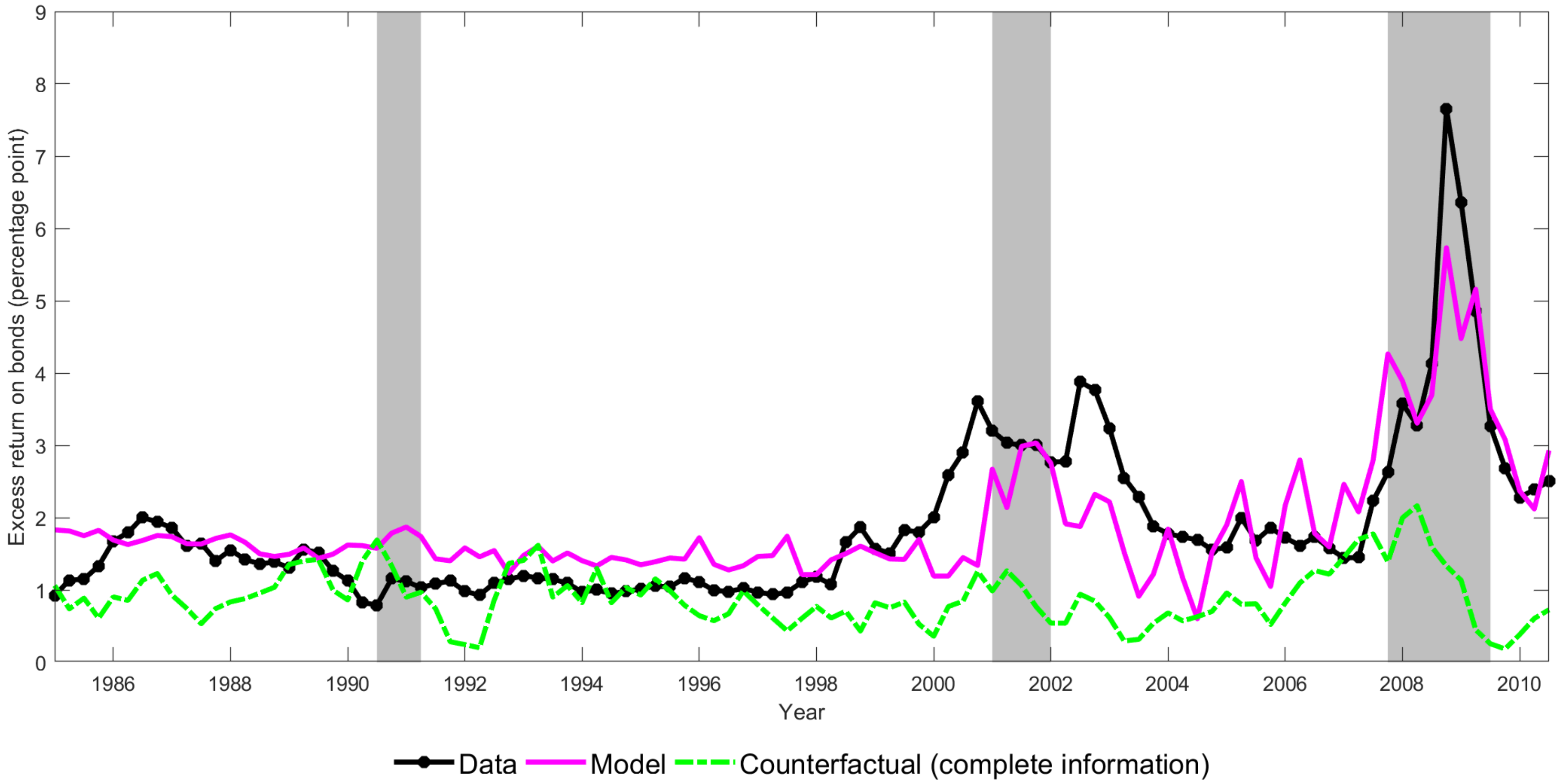
Note: Panel A reports the targeted moments in the baseline model with information frictions and rational learning, and their data counterparts. Panel B reports the untargeted fit of the model, including both first and second moments. The data moments are calculated from the Compustat between 1985Q1 and 2010Q4.

Table 10: Aggregate Moments in Models With and Without Information Frictions

	Data (1)	**With information frictions** (2)	**Without information frictions** (3)
First moments			
Default rate	0.013	0.010	0.012
Bond spread	0.019	0.023	0.016
Leverage	0.267	0.305	0.335
Investment	0.018	0.023	0.029
Second moments			
Corr(default, output)	−0.43	−0.17	0.32
Corr(spread, output)	−0.57	−0.39	0.46
Corr(invest, output)	0.57	0.74	0.71
σ(spread)/σ(output)	2.10	2.41	1.93
σ(invest)/σ(output)	3.46	2.75	2.28

Note: This table compares the model-generated moments in the model with and without learning. The difference between the two models lies in the bond pricing equation. In the baseline model with rational learning, the price of debt (given by 18) is a function of the public signal (s_t). In the model without information frictions, investors can observe the firm-specific profit shock z_t after its realization so the price of debt (given by (10)) is a function of z_t.

Figure 5: Historical Bond Spread: Data vs. Model (1985Q1–2010Q4)



Note: This figure shows the time series of corporate bond spread in the US between 1973Q1 and 2010Q4, comparing the data series and two different model-implied series: one from the imperfect information model with rational learning, and the other from the model without information frictions. Shaded areas indicate the NBER recession dates.

Table 11: Aggregate Moments in Rational Learning Model with "Noisier" Signals

	Baseline	Counterfactuals		
	(1)	(2)	(3)	(4)
	$[\sigma_u^2,\ c_e]$	$[2\sigma_u^2,\ c_e]$	$[2\sigma_u^2,\ 2c_e]$	$[\sigma_u^2,\ 2c_e]$
First moments				
Default rate	0.010	0.008	0.018	0.022
Bond spread	0.023	0.036	0.047	0.033
Leverage	0.305	0.267	0.311	0.370
Investment	0.023	0.018	0.017	0.021
Second moments				
Corr(default, output)	−0.17	−0.24	−0.21	−0.13
Corr(spread, output)	−0.39	−0.35	−0.28	−0.20
Corr(invest, output)	0.74	0.65	0.68	0.70
σ(spread)/σ(output)	2.41	3.35	3.49	2.53
σ(invest)/σ(output)	2.75	2.87	3.04	2.72

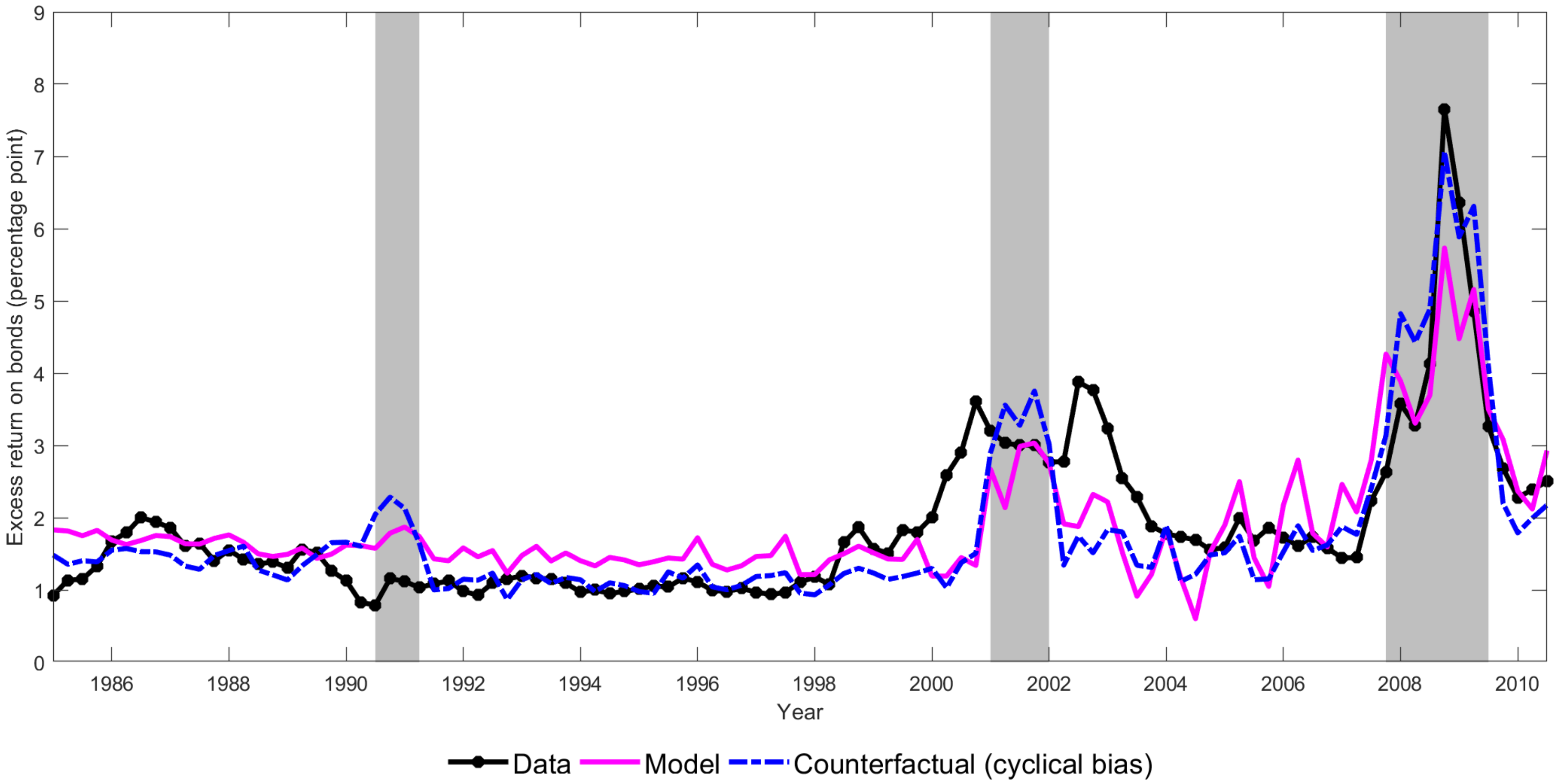
Note: This table compares the model predictions under different parameterization of σ_u (the noisiness of the signal) and c_e (the cost of equity financing) under rational learning. Column (1) presents the moments under the baseline calibration, as reported in Table 7. We consider three counterfactuals: in columns (2) and (3), σ_u^2 is doubled; in columns (3) and (4), c_e is doubled.

Table 12: Aggregate Moments with Alternative Learning Rules

Moments	**Rational (Baseline)** (1)	**Near-Rational** (2)	**Systematically Optimistic** (3)	**Systematically Pessimistic** (4)	**Cyclical Bias** (5)
First moments					
Default risk	0.010	0.012	0.013	0.008	0.011
Bond spread	0.023	0.024	0.017	0.031	0.025
Leverage	0.305	0.302	0.321	0.289	0.298
Investment	0.023	0.022	0.026	0.020	0.022
Second moments					
Corr(default, output)	−0.17	−0.14	−0.08	−0.11	−0.22
Corr(spread, output)	−0.39	-0.26	−0.15	−0.21	−0.49
Corr(invest, output)	0.74	0.70	0.68	0.67	0.79
σ(spread)/σ(output)	2.41	2.75	1.95	2.11	3.12
σ(invest)/σ(output)	2.65	2.94	2.48	2.53	3.31

Note: This table compares the model predictions under different learning rules. Compared to the rational learning benchmark (column (1)), we consider four alternative learning rules, where investors are near-rational (column (2)), systematically optimistic (column (3)) and pessimistic (column (4)), and the scenario where investors are more optimistic in booms and pessimistic in recessions (column (5)).

Figure 6: Historical Bond Spread: Data vs. Model with Cyclical Bias (1985Q1–2010Q4)



Note: This figure shows the time series of corporate bond spread in the US between 1973Q1 and 2010Q4, comparing the data series and two different model-implied series: one from the rational learning model with the baseline calibration, and the other from the model with cyclical bias, whereby investors are more pessimistic in recessions and optimistic in booms. Shaded areas indicate the NBER recession dates.