The Expectations Driven Financial Accelerator*

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Abstract

This paper develops a unified quantitative account of credit cycles and their macroeconomic consequences based on information frictions in debt markets. Using a dynamic model with endogenous default, we highlight a novel "herding" mechanism whereby uninformed debt investors learn about firms' creditworthiness from publicly-available survey information on quarter-ahead corporate profits. We show that: 1) short-term changes in expectations of corporate profits strongly forecast credit spreads and real economic aggregates over up to two years horizons; 2) credit spreads and defaults are counter-cyclical; 3) the mechanism can account quantitatively for the historically large spike in spreads during the financial crisis.

JEL codes: D84, G12, G30, E32

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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 has 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 perfect information. 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 perfect information.

The unique mechanism at the core of our model of credit cycles is testable and our first contribution is to document new stylized facts that we will use as one of the benchmarks to evaluate the quantitative performance of the model. First, 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 US 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.

Second, 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 (Hennessy and Whited, 2007, 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 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; second, credit-market investors' beliefs about the firm's creditworthiness affect debt pricing and, thus, firm leverage and investment decisions.[1] These two

[1]To clarify language, the use of "herding" throughout the paper is shorthand for "rational herding" or "informational learning," because in our model credit market investors learn about the views of others using publicly-available information and do not directly mimic the behavior of others (for examples of information-based learning, see Froot, Scharfstein, and Stein, 1992. Lorenzoni, 2009, and

stark ingredients have powerful implications. For a realistic parametrization that is calibrated to match average investment, leverage, profitability, and default rates, we show that the model successfully replicates the sign and magnitudes of the predictive regression results that we documented in the data – i.e., a deterioration in short-term expectations of corporate profits leads to a lasting widening of credit spreads and to an economic contraction in investment and output.

In addition, 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 are counter-cyclical. 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 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 and is closely aligned with its empirical counterpart. Importantly, these results are not sensitive to the details of how exactly credit market investors form their beliefs, holding robustly across several alternative deviations from rational learning that include optimism, pessimism, near-rational, and extrapolative learning. 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 two main contributions. First, we contribute to the literature on investment-based bond pricing (e.g., Kuehn and Schmid, 2014, Gomes and Schmid, 2017) and, more specifically, to the literature on investment and bond pricing over the business cycle (Gomes, Grotteria, and Wachter, 2019) by introducing a new modeling feature, investors' learning, and showing that it constitutes a useful ingredient to improve the business cycle performance of this class of models and their fit with the growing evidence of time-series predictability including ours.[2] A recent literature has started to explore learning in equity markets (see, for example, Adam, Marcet, and Beutel, 2017), but we know relatively little about the role of learning in credit markets. By doing so, we also contribute a quantitative model to the classical literature

Angeletos and La'O, 2013 are related information-based models of business cycle fluctuations).

[2]By linking investment and financing decisions to changes in the cost of debt financing, we also contribute to the literature on misvaluation and market timing (Warusawitharana and Whited, 2016, Bolton, Chen, and Wang, 2013), which has so far mainly focused on equity markets.

on learning and herding in finance (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).[3] Our results suggest that informational inefficiencies and investor learning are critical to understand large volatility episodes in debt markets and their consequences for the macroeconomy.

Second, we contribute a quantitative model to the recent research in finance and macroeconomics on 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. López-Salido, Stein, and Zakrajšek (2017) show that fluctuations in credit market sentiment are closely tied to future movements in aggregate economic activity. These papers show important and convincing evidence that credit market sentiment matters, but the ultimate sources of sentiment are relatively unknown. And the primary approach in this literature so far has been mainly empirical, which leaves open the question of quantifying the importance of a given source of credit market sentiment for cycles. Our contribution is to highlight learning by credit-market investors as a source of sentiment, and to take a first step toward quantifying its importance for credit cycles.

An additional advantage of our rational-learning benchmark is that it can be used to quantify the relative contribution of different mechanisms that drive credit cycles, including behavioral deviations from rationality. The main takeaway from our analysis is that learning represents one potentially important force at play, but, of course, there are likely other mechanisms that matter. As such, learning does not negate but rather complements existing behavioral explanations, such as extrapolative expectations (Bordalo, Gennaioli, and Shleifer, 2018, Bordalo, Gennaioli, Shleifer, and Terry, 2019, Greenwood, Hanson, and Jin, 2019). Our model extensions that consider alternative types of learning are a first step in the direction of exploring the intriguing question of the relative importance of rational versus behavioral explanations of credit cycles. While the results indicate that behavioral factors such as pessimism and extrapolation are also quantitatively important, clearly much more can be done to further extend our framework and size up the relative contribution of different sources of credit market sentiment and their impact on the real economy.

[3]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.

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, followed by a discussion on the quantitative implications of the model on corporate investment and credit spreads. Section 6 deviates from rational expectations, and considers the aggregate implications of near-rational learning and behavioral biases in debt markets. Section 7 concludes.

2 Stylized Facts

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.

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, 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.

2.1 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:

$$R_{t\rightarrow t+k} = \alpha + \beta X_t + u_{t+k}, \quad (2)$$

where $R_{t\rightarrow t+k}$ 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. 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:

$$R_{t\rightarrow t+k} = \alpha + \beta X_t + \gamma Controls_t + u_{t+k}, \quad (3)$$

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 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 changes in excess return (in percentage point) associated with a one standard deviation revision in expectations Rev_t, or its dispersion σ_t. For instance, Table 2 reports that a one standard deviation upward revision in investors' expectations lowers the excess return on corporate bonds by about 25 basis points in the following quarter, whereas a one standard deviation increase in the dispersion of revisions raises the spread by about 63 basis points, which are respectively about 15 percent and 40 percent of the unconditional mean of spreads in our sample (1.6 percentage points). To provide an alternative assessment of economic significance of the effects, 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 estimates imply that the combined effect of downward revisions and higher dispersion raised spreads by 2 percentage points ($0.246\times0.44+0.627\times3$), on average, in that period.

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.

2.2 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, business investment, consumption and employment growth (Tables 4 and 5). 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:

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

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 3) using either our 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 4 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 4 confirm the finding of López-Salido, Stein, and Zakrajšek (2017) that credit spreads are a strong predictor of business cycle variables.

The combined magnitudes of the first stage estimates in Table 3 and the second stage estimates in Table 4 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 3 and 4 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 ($-0.277\times-0.064\times0.44-0.338\times-0.343\times 3$), on an average quarterly basis, in that period.

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 information frictions. 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 the firm's creditworthiness. Instead, investors form beliefs about it by "following the herd" – i.e., using publicly-available information on quarter-ahead corporate profits from surveys of professional forecasters. In what follows, we provide a model framework to study how rational herding by credit market investors – as they learn about the views of others using publicly-available information – can affect corporate bond pricing and, thus, firm leverage and investment decisions.[4]

3.1 Economic Environment

A. Technology and Income Processes

Time is discrete and the horizon infinite. A firm produces output y using decreasing returns to scale technology:

$$y = ak^{\alpha}, \text{ with } \alpha < 1,$$

where k is the capital input, and a is aggregate productivity. After production, the firm receives a shock to their cost of operation z, so its operating profit before tax in each period is:

$$\Pi = ak^{\alpha} - z.$$

We assume discrete processes for aggregate productivity and cost of operation shocks that approximate the following autoregressive processes, respectively:

$$\log a' = \rho_a \log a + \varepsilon'_a \tag{4}$$

$$z' = \mu_z + \rho_z z + \varepsilon'_z, \tag{5}$$

where μ_z is the mean cost of operation, and the innovations, $\varepsilon'_a \sim N(0, \sigma_a^2)$ and $\varepsilon'_z \sim N(0, \sigma_\varepsilon^2)$, are independent. Capital accumulation follows:

$$k' = (1 - \delta)k + i,$$

[4]This paper is related to information-based models of business cycle fluctuations, such as Eusepi and Preston (2011), Lorenzoni (2009), Jaimovich and Rebelo (2009) and Angeletos and La'O (2013). 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 for the real economy.

subject to a quadratic investment adjustment cost:

$$g(k,k') = \frac{c_k}{2}\Big(\frac{k' - (1-\delta)k}{k}\Big)^2 k.$$

B. Costs of 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. In every period, it is required to pay back a fraction λ of the principal, 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. Thus, investors buy corporate debt at price q, and they collect coupon and principal payments, $(c+\lambda)b'$, 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 $(1-\tau)(a'k'^{\alpha} - z')$, the total enterprise value $V'(\cdot)$, and the market value of remaining debt $(1-\lambda)q'b'$, net of the deadweight loss $\xi k'$, with $\xi \in (0,1]$.

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

$$\Lambda(e) = 1_{e<0} c_e e \qquad (6)$$

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

C. Information Frictions in Debt Markets

We assume that bond investors observe the realization of aggregate productivity a, the firm's policy functions (b',k'), and they know the structure of the economy, including the law of motion for z (5), but they do not observe the realization of z, which is only known to the firm. Instead, investors observe a signal s of its innovation ε_z, knowing that s follows the process:

$$s = \rho_s s_{-1} - \varepsilon_z + u. \tag{7}$$

The noise in the signal, u, is i.i.d. normal with zero mean and variance σ_u^2. ε_z and u independent. After observing s, investors can use the laws of motion for z (5) and s (7) to form an estimate of z (denoted by $\tilde{z}$) using the following relation:

$$\tilde{z}(\mathcal{S}) = \mathrm{E}\big[z|\mathcal{S}\big] = \frac{\mu_z}{1-\rho_z} - \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_u^2} \sum_{j=0}^{\infty} \rho_z^j \Big(s_{-j} - \rho_s s_{-j-1}\Big), \tag{8}$$

given the history of s up to the current period, $\mathcal{S} = \{s_0, s_1, ..., s\}$. Hence the information set of debt investors at time t includes the history of all the model variables through time t but not the current and past realizations of ε_z. See Appendix A for details.

3.2 Firm's Problem

In each period, the equity holders can default on their debt obligation if the equity value of the firm $J(k', b', z', a', \tilde{z}')$ falls below zero. This pins down a cutoff level z'^* that satisfies:

$$J(k', b', z'^*, a', \tilde{z}') = 0 \tag{9}$$

such that the firm repays if $z' \leq z'^*(k', b', a', \tilde{z}')$, and defaults otherwise. The equity value $J(\cdot)$ consists of two parts (e.g. Gomes, Jermann, and Schmid, 2016):

$$J(k,b,z,a,\tilde{z}) = \max \Bigg[0,\ \underbrace{(1-\tau)\big(ak^\alpha - z\big)}_{\text{after-tax profit}} - \underbrace{\big(c+\lambda\big)b}_{\text{debt payment}} + \underbrace{\tau\big(\delta k + cb\big)}_{\text{tax rebate}} + \underbrace{V(k,b,z,a,\tilde{z})}_{\text{continuation value}}\Bigg], \tag{10}$$

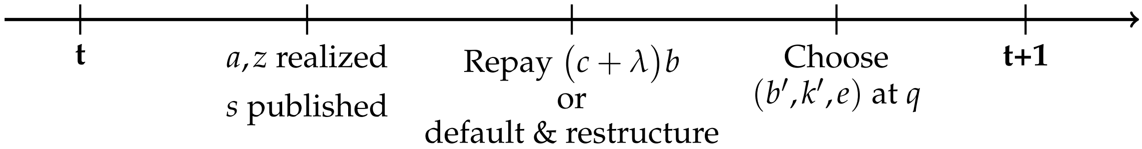

Figure 1: Timing

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

$$V(k,b,z,a,\tilde{z}) = \max_{b',k',e} \Bigg\{ \underbrace{q(b',k',\tilde{z},a)\Big(b' - (1-\lambda)b\Big)}_{\text{value of new debt issues}} - \underbrace{\Big(k' - (1-\delta)k\Big) - g(k,k')}_{\text{investment and adj. cost}} \underbrace{+\Lambda(e)}_{\text{equity issuance cost (6)}} + \underbrace{\beta \int_{\underline{a}}^{\overline{a}} \int_{\underline{z}}^{\overline{z}} \int_{\underline{z}}^{z'^{*}(k',b',a',\tilde{z}')} J\big(k',b',z',a',\tilde{z}'\big) \;\; P(z,dz')P(\tilde{z},d\tilde{z}')Q(a,da')}_{\text{expected future equity value}} \Bigg\}. \tag{11}$$

The definition of equity payout / issuance is given by:

$$e = (1-\tau)\big(ak^{\alpha} - z\big) - \big(c+\lambda\big)b - \big(k' - (1-\delta)k\big) - g\big(k,k'\big) + \tau\big(\delta k + cb\big) + q(b',k',\tilde{z},a)\Big(b' - (1-\lambda)b\Big), \tag{12}$$

where $q(b',k',\tilde{z},a)$ is the current market price of one unit of debt, so $\big(b' - (1-\lambda)b\big)$ is the market value of new debt issues in the current period. $P(z,dz')$, $P(\tilde{z},d\tilde{z}')$ and $Q(a,da')$ are the transition functions of z, $\tilde{z}$ and a, respectively. Both z and $\tilde{z}$ take values over the interval $[\underline{z}, \overline{z}]$, and a over $[\underline{a}, \overline{a}]$.

The timing of the problem is shown in Figure 1. At the beginning of each period, the firm carries debt b and capital k for the current period's production. Upon observing the shocks a and z, its profit Π is realized, and the firm faces the decision whether or not to repay its debt obligation, $\big(c+\lambda\big)b$. 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, investors sell off the equity portion to new owners, who then choose b', k', and e.

Bond investors observe a and s when the firm observes a and z. Investors form their estimate of the firm's latent state $\tilde{z}$ according to (8). As they observe b' and k', they use their estimate $\tilde{z}$ to determine the price of bond $q(b',k',\tilde{z},a)$ before the end of the period.

3.3 Pricing of Corporate Bonds

The price of bond b' raised in t follows the no-arbitrage condition:[5]

$$
\begin{aligned}
q(b',k',\tilde{z},a) \\
= \beta \Bigg\{ & \int_{\underline{a}}^{\overline{a}} \int_{\underline{z}}^{\overline{z}} \int_{\underline{z}}^{\tilde{z}'^*(k',b',a',\tilde{z}')} \Big[c + \lambda + (1-\lambda) q'(b'',k'',\tilde{z}',a') \Big] P(\tilde{z},dz') P(\tilde{z},d\tilde{z}') Q(a,da') \\
& + \int_{\underline{a}}^{\overline{a}} \int_{\underline{z}}^{\overline{z}} \int_{\tilde{z}^*(k',b',a',\tilde{z}')}^{\overline{z}} B(b',k',z',a',\tilde{z}') \; P(\tilde{z},dz') P(\tilde{z},d\tilde{z}') Q(a,da') \Bigg\}. \qquad (13)
\end{aligned}
$$

Since investors cannot observe z, the price of debt q is a function of investors' estimate $\tilde{z}$, instead of the actual z. Whether the firm repays or defaults in the next period depends on the realization of z', and $P(\tilde{z},dz')$ indicates the transition probabilities from z to z' when investors perceive z to be $\tilde{z}$. $B(b',k',z',a',\tilde{z}')$ is the recuperation rate of bond that takes the value between 0 and the maximum recovery rate $B_{\max}$:

$$
\begin{aligned}
B(b',k',z',a',\tilde{z}') = \min \Bigg[\max \Big[0, \Big((1-\tau)\big(a'k'^{\alpha} - z'\big) \\
+ V(k',b',z',a',\tilde{z}') + (1-\lambda) q'(b'',k'',\tilde{z}',a') b' - \xi k' \Big) \frac{1}{b'} \Big], \; B^{\max} \Bigg]. \qquad (14)
\end{aligned}
$$

3.4 Recursive Competitive Equilibrium

A recursive competitive equilibrium in this economy consists of: (1) value of the firm $J(b,k,z,a,\tilde{z})$ and the continuation value $V(b,k,z,a,\tilde{z})$; (2) policy functions $b'(b,k,z,a,\tilde{z})$, $k'(b,k,z,a,\tilde{z})$, e; (3) bond pricing schedule $q(b',k',\tilde{z},a)$, such that:

1. $b'(b,k,z,a,\tilde{z})$, $k'(b,k,z,a,\tilde{z})$, e, $J(b,k,z,a,\tilde{z})$, and $V(b,k,z,a,\tilde{z})$ satisfy the firm's op-

[5] With long-term debt, the price of debt depends on future debt prices q' and thus on next period's leverage and investment choices (b'',k''). Time consistency requires that next period's leverage and investment be functions of the current optimal policy (e.g. Gomes, Jermann, and Schmid, 2016).

timization problem (10) and (11), given the bond pricing schedule $q(b',k',\tilde{z},a)$;

2. $q(b',k',\tilde{z},a)$ satisfies the break-even condition (13) subject to (8) and (14), given the law of motion for the signal (7), and the history of signals $\mathcal{S} = \{s_0, s_1, ..., s\}$.

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. Since our focus is on the impact of information frictions on the supply of bonds, so in this section we take a partial equilibrium approach and take the firm's demand for bonds as given – an assumption that is relaxed in the quantitative model.

4.1 Investors' Problem

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

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

with a recovery rate in default of $\tilde{B} < 1$. We assume in this section that the default probability $1 - p_{t+1}$ and the recovery rate $\tilde{B}$ are exogenous – an assumption that is relaxed in the quantitative model where default is endogenous.

The key friction is that 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:

$$\begin{aligned} q_t &= \beta \mathrm{E}_t \left[p_{t+1} + \tilde{B}(1 - p_{t+1}) \middle| s_t \right] \\ &= \beta \Big(\tilde{B} + \Big(1 - \tilde{B}\Big) \mathrm{E}_t \Big[p_{t+1} \Big| s_t \Big] \Big) \\ &= \beta \left(\tilde{B} + \Big(1 - \tilde{B}\Big) \left[\bar{p} + \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_u^2} s_t \right] \right). \end{aligned} \tag{15}$$

If the investors are risk-neutral, the spread between the risky bond and the risk-free bond is given by:[6]

$$\begin{aligned} \tilde{R}_{t+1} &= \mathrm{E}_t \left[1 - x_{t+1} \middle| s_t \right] \\ &= \Big(1 - \mathrm{E}_t \Big[p_{t+1} \Big| s_t \Big] \Big) \Big(1 - \tilde{B} \Big) \\ &= \left(1 - \left[\bar{p} + \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_u^2} s_t \right] \right) \Big(1 - \tilde{B} \Big) \\ &= \underbrace{(1 - \bar{p}) \Big(1 - \tilde{B} \Big)}_{\text{default premium}} - \underbrace{\frac{\sigma_\varepsilon^2 \Big(1 - \tilde{B} \Big)}{\sigma_\varepsilon^2 + \sigma_u^2} s_t}_{\text{learning}} \end{aligned} \tag{16}$$

Therefore, equation (16) shows that 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. Ceteris paribus, the spread is higher when the signal is more pessimistic (lower s_t) or if the signal series becomes noisier (higher σ_u^2). It is also immediate from equation (16) that the volatility of spread is increasing in the volatility of the signal.

4.2 Bond Market Equilibrium

In a world without asymmetric information where investors can perfectly observe the repayment probability, the price of bond is simply a function of p_{t+1}:

$$q_t = \beta \Big(\tilde{B} + (1 - \tilde{B}) p_{t+1} \Big). \tag{17}$$

[6]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.

This captures investors' demand for bonds without information frictions. In a general equilibrium setting where the repayment probability p_{t+1} is endogenous, p_{t+1} is decreasing in the level of borrowing b_{t+1}. In other words, a firm is closer to default if it is more leveraged, so the demand for bonds is downward sloping. In this partial equilibrium setting, we assume for simplicity that the firm's supply of bonds is fixed at $\bar{b}_0$, so the supply curve is vertical, and the bond market equilibrium is denoted by $(q_0^*, \bar{b}_0)$, as shown in Figure 2.

In technology-driven real business cycle models with costly external finance, empirically plausible parameterization often leads to procyclical credit spreads. This result runs counter to the data, as discussed by Gilchrist, Sim, and Zakrajšek (2014), and Gomes, Yaron, and Zhang (2003). 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. Relating this to our simple example above, a negative TFP shock that reduces the firm's needs borrowing represents leftward shift in the supply of bonds: the firm has fewer investment opportunities so issues fewer bonds at every q_t. As a result, the bond market equilibrium shifts to $(q_1^*, \bar{b}_1)$. Since the bond pricing function (15) is downward sloping, the new equilibrium features a higher bond price and hence a counterfactually lower spread in an economic downturn, as shown in Panel (a) of Figure 2.

Now, going back to our example with asymmetric information where p_{t+1} is not observed by investors, the price of bond q_t is a function of the firm's mean default probability $\bar{p}$, and importantly, the signal s_t. Since investors can observe the amount of bonds issued by the firm, it is reasonable to assume that the relation between p_{t+1} and b_{t+1} is public information, and is reflected in the mean default probability $\bar{p}$ that is observable by the investors. Panel (b) of Figure 2 shows the determination of bond market equilibrium in the world with asymmetric information.

If the signal s_t is procyclical, then the schedule for q_t shifts downward in a recession: Ceteris paribus, q_t is lower at every level of b_{t+1} as investors learn from a more pessimistic signal s_t. Therefore, the public signal counteracts the impact of a reduction in the supply of bonds (from $\bar{b}_0$ to $\bar{b}_1$) on q_t. Changes in signals share the features of demand shocks, since the equilibrium price and quantity move in the same direction in response to them.[7] Quantitatively, which force dominates is ambiguous, and

[7] In this respect, we share a similar interpretation of business cycles as Lorenzoni (2009), who shows

depends on how large the shifts are and how elastic the curves are. For instance, if the signal is more pessimistic than the actual decline in productivity, the shift in demand is more likely to dominate the shift in supply, leading to investors' "over-reaction" and spikes in credit spreads, as we saw in the 2007-09 financial crisis.

To sum up, in this section we highlight two features of a simplified bond pricing model with information frictions and learning:

1. Credit spreads are higher when investors receive a more pessimistic signal about firms' creditworthiness, or if the signal series becomes noisier;

2. If signals are procyclical, then credit spreads are more likely to be countercyclical, as we observe in the data.

In the following section, we show that the impact of learning on credit spreads can dominate the impact of procyclical productivity shocks on firms' financing needs, under realistic calibration of a dynamic firm financing model to the U.S. data.

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 Parameterization

The model is calibrated at quarterly frequency and the sample period is from 1985Q1 to 2010Q4. There are 17 parameters in the benchmark model with rational learning:

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

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

that cyclical fluctuations can be driven by shocks to expectations. However, the underlying mechanism as well as the environment in which it works are different. In Lorenzoni (2009), "noise shocks" affect the real economy by changing consumers' expectations and nominal rigidities play an important role, whereas in our model, the mechanism is embedded in the pricing of debt by investors and incomplete markets play a crucial role.

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 six parameters $\{\lambda, B^{\max}, \rho_a, \sigma_a, \rho_z, \sigma_\varepsilon\}$ 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, similar to the value used in Gomes, Jermann, and Schmid (2016). To ensure that debt remains risky when the firm become large, we cap the recovery rate of bonds, $B^{\max}$, at 69 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). 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.

Our empirical proxy for the signal observed by bond investors is the current revision in professional forecasters' expectations of quarter-ahead corporate profits, to capture the new information available to forecasters in each period. Figure 3 plots this series from the Survey of Professional Forecasters between 1970Q1 and 2010Q4. We determine σ_u using the following relation:

$$\sigma_u^2 = (1 - \rho_s^2)\sigma_s^2 - \sigma_\varepsilon^2 \tag{18}$$

which comes from equation (7), under the assumption that ε_t and u_t are independent. To obtain estimates of $\{\rho_s, \sigma_s\}$, we first compute the percentage change in forecasters' expectations of the quarter-ahead corporate profits, i.e. $s_t = \ln \mathrm{E}_t(\Pi_{t+1}) - \ln \mathrm{E}_{t-1}(\Pi_{t+1})$.[8] It is worth mentioning that we estimate the learning parameters using an expanding window: for each quarter, we estimate σ_s and ρ_s 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 $\mathcal{S} = \{s_0, s_1, ..., s\}$ to estimate the learning parameters. With the estimates for σ_s and σ_ε, we then use relation (18) to compute the volatility of noise σ_u, which also varies over time.

The last four parameters $\{\xi, \mu_z, c_e, c_k\}$ are calibrated to target the mean default rate,

[8] We test the empirical distribution of the residuals from the following regression:

$$s = \rho_s s_{-1} + \eta,$$

and the Kolmogorov-Smirnov test statistic (with p-value = 0.4541) cannot reject the null hypothesis that the residuals are normally distributed with mean 0 and standard deviation 0.06 for the whole sample period.

mean profit-to-asset ratio, mean leverage ratio, and 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.

We discretize the shocks using Tauchen (1986). Since the model is nonlinear, we solve it globally. For a given set of values for $\{\xi, \mu_z, c_e, c_k\}$, we first solve for the policies of the firm by value function iterations (see Appendix B for details). Then we compute the targeted moments by simulating data using the realized series of technology (z), the revision series (s), the estimated series of the learning parameters (ρ_s and σ_u), and the firm's policies 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 $\{\xi, \mu_z, c_e, c_k\}$. The parameter values in the baseline model with rational learning are summarized in Table 6. In addition, Table A.1 reports the empirical estimates of ρ_s and σ_u for each quarter between 1985Q1 and 2010Q4.

5.2 Model Fit

Table 7 presents 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, default rates, and investment. The 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 despite the low default rate associated with the long-term debt. Moreover, the model can generate countercyclical spreads without imposing time-varying default costs or introducing other types of aggregate shock.

Next we 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. The model produces fluctuations in credit spreads that provide a good fit to those in the data, especially during the 2007-09 financial crisis.

As an additional test for model fit, we run our baseline regression (2) using the model-implied credit spreads and the same measure of expectations Rev_t as in our empirical analysis for the period 1985Q1-2010Q4. The results are presented in Table 8. 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 20 basis points (Panel A). Moreover, 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

Table 9 compares the moments generated from the imperfect information model with those from a counterfactual model in which bond investors have the same information set as the firm.[9] We show that informational inefficiencies in the debt markets have three main effects on corporate bond spreads.

First, spreads are significantly lower in the perfect information model, compared to both our baseline model and 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 when investors are uncertain about the firm's default probability, they demand higher premia. While this mechanism is absent in standard firm financing models with only financial frictions, it allows the imperfect information model to match the average default rate and spread simultaneously.

Second, spreads are more volatile when investors cannot observe the latent state of the firm, especially during recessions. Moreover, Figure 5 shows that the volatilities of spreads in the model with perfect information 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 model with information frictions generates the "spikes" in the more recent recessions, since the measured expectation was more volatile in the 2000s than in the 1980s (see Figure 3). The model with information friction captures the time variation in bond spreads as investors learn about s_t, σ_u and ρ_s over time.[10]

[9] See Appendix C for the setup of the perfect information model.

[10] In the baseline model, bond investors use the signal series s_t to "learn" about z_t, σ_u and ρ_s over time. For robustness, we simulate an alternative model in which investors only use s_t to learn about z_t over time, whereas σ_u and ρ_s are fixed, as we calibrate them externally using the entire sample of observations, yielding $\sigma_u = 0.048$ and $\rho_s = 0.264$. The simulation results are presented in Figure A.1. As shown in Table A.1, the volatility of noise in the signal increases above 0.048 from 2004, noisier signals amplified the increase in credit spreads during the 2007-09 financial crisis.

Third, without information frictions, credit spreads are procyclical in a technology-driven business cycle model with costly external finance, but it is well documented that corporate bond spreads are strongly countercyclical in the data. This is because an adverse technology shock reduces profitable investment opportunities, and therefore lowers a firm's incentive to borrow, and in turn, its default risk and spread. As shown in column (3) of Table 9, both spreads and default rates are procyclical in the counterfactual model with perfect information. By contrast, the imperfect information model can generate countercyclical spreads, even with TFP shocks as the only source of aggregate fluctuations. This is because the measured expectations are highly procyclical, and the spreads react negatively to them. As shown in Figure 2, when investors receive an adverse signal about the firm, the bond pricing schedule shifts inward, and both the price (q_t) and quantity (b_{t+1}) of bonds would fall. This effect quantitatively dominates the effect of a reduction in firm's leverage on the equilibrium price, because the signals are not only procyclical, but also more volatile in recessions (see Figure 3).

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). In the first exercise, we double σ_u and re-simulate the model, keeping the rest of the parameters unchanged. Next, we double σ_u as well as c_e. In the last exercise, we only double c_e and leave σ_u unchanged. Table 10 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 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 model (column 3), 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 in borrowing costs. As a result, there is less external financing in total and aggregate investment is lower.

Comparing across Table 10, we see that higher leverage implies higher credit spreads ($2.8 - 1.7 = 1.1$ percentage points), but the additional impact of having noisier signals is stronger ($4.6 - 2.8 = 1.8$ percentage points). Similarly, the decline in investment due to noisier signals ($1.5 - 2.1 = -0.6$ percentage points) is larger than the decline due to more expensive external financing alone ($2.1 - 2.4 = -0.3$ percentage points). These comparative static exercises suggest 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.

6 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 three types of behavioral biases that distort investors' expectations of the firm's latent state.[11] 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 11 summarizes the model-implied moments under these alternative learning rules.

[11] 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.

6.1 Optimism and Pessimism

In our context, we say that investors are "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 investors observe the signal s, they update their belief about z according to:

$$\tilde{z}^{\text{bias}} = \tilde{z} + \psi, \tag{19}$$

where ψ is a constant and $\tilde{z}$ is from the rational learning model defined in (8). For pessimistic investors, ψ is positive (denoted as ψ_p); in other words, compared to a rational investor, their estimate of the firm's cost of operation z is higher. By a similar argument, if investors are optimistic, ψ is negative (denoted as ψ_o). Such behavioral bias affects bond prices via the transition probabilities $P(\tilde{z}^{\text{bias}}, dz')$ and $P(\tilde{z}^{\text{bias}}, d\tilde{z}')$ in equation (13), with $\tilde{z}^{\text{bias}} \neq \tilde{z}$.

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.[12] 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, profit-to-asset ratio, leverage ratio, investment rate), but now we distinguish between investment-grade and speculative-grade firms. Tables A.2 and A.3 summarize the parameter values in each set of calibration. Columns (3) and (4) of Table 11 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 2.06% in the model. Moreover, introducing biased beliefs does not overturn the model prediction that spreads are countercyclical.

[12] In the baseline model, we use the bankruptcy cost parameter ξ to target the mean default rate. Here we calibrate ξ externally, using a common value used in the literature (see Tables A.2 and A.3).

6.2 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 is still conditionally unbiased.

The timing of investors' problem is the same as the rational learning case. Once they observe the public signal s, they update their belief about z according to:

$$\tilde{z}^{\text{NR}} = (1-\omega)\tilde{z} + \omega\eta, \tag{20}$$

where $\tilde{z}$ is from the rational learning model, as defined in (8), η 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.

We solve the model under the new updating rule (20), under the same parameterization as the baseline model with rational learning (Table 6). In addition, we perform comparative statics analysis by calibrating two different values for ω in turn, such that agents update their beliefs correctly 90 percent ($\omega = 0.1$) and 70 percent ($\omega = 0.3$) of the time, respectively. We simulate the model for the sample period and compute the aggregate moments reported in columns (5) and (6) of Table 11.

The main differences from the baseline model are 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 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.

6.3 Overextrapolation

In our context, extrapolative investors believe signals to be more persistent than they actually are. Formally, they believe the signal persistence parameter in equation (7) to be $\rho_s^B > \rho_s$, and use ρ_s^B in forming their estimate of z according to the updating equation (8). Let the difference $\zeta = \rho_s^B - \rho_s$ measure the degree of overextrapolation. 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 6). We use empirical estimates of overextrapolation from

Landier, Ma, and Thesmar (2019) to calibrate ζ.[13]

Quantitatively, the last two columns of Table 11 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 half of the correlation between spread and output in the data, whereas the model with overextrapolation can account for about three-quarters of it. Hence the relative contribution of overextrapolation is approximately one-quarter. By the same logic, the relative contribution of overextrapolation in explaining the correlation between default and output is about 20 percent.

Besides improving business cycle correlations, overextrapolation further increases the level and volatility of spreads. Since the signal series is symmetrically distributed, overextrapolative investors' estimates of z may be higher or lower than rational investors' estimates depending on the realization of s, so the volatility of spreads increases. Moreover, due to the concavity in investors' payoff function, overextrapolation in bad states has greater impact on credit spreads than in good states, so the mean spread increases unambiguously with overextrapolation despite the signal series being symmetric. Put differently, the distribution of credit spreads are right-skewed, as in the data. If investors are overextrapolative, the distribution shifts to the right, resulting in an increase in the mean spread during the sample period.

7 Conclusion

In order to better understand the consequences of informational inefficiencies in credit market, we have combined time-series data on professional forecasts of corporate profits, bond returns, and macroeconomic outcomes with a novel "herding" 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

[13]In Landier, Ma, and Thesmar (2019), the degree of overextrapolation relative to extrapolation is approximately two-thirds. Since our estimates of ρ_s are between 0.24 and 0.31, this implies that for overextrapolative investors ρ_s^B should be between 0.4 and 0.52, and the degree of overextrapolation ζ is between 0.16 and 0.21.

that incorporates this mechanism and shown that its ability to account for key stylized facts of the credit cycles is superior to the perfect information benchmark. In all, our model provides a novel mechanism through which information frictions in credit markets 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 and imperfect information are central themes in modern financial economics going back to Keynes (1936) and Minsky (1977, 1986).

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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 to 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 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 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.

	Rev_t					σ_t				
Panel A: Excess Return on Corporate Bonds										
	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										
	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										
	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:

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

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 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 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.

	Rev_t					σ_t				
Panel A: Excess Return on Corporate Bonds										
	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										
	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										
	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 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, $\widehat{R}_{t\to t+k}$ 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.

	Rev_t				σ_t			
Panel A: Excess Return on Corporate Bonds								
	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								
	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								
	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:

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

$\widehat{R}_{t\rightarrow t+k}$ is estimated from the multivariate forecasting regression of credit spreads, $R_{t\rightarrow t+k} = \alpha + \beta X_t + \gamma Controls_t + u_{t+k}$, 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 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, $\widehat{R}_{t\rightarrow t+k}$ is the predicted 4- or 8-quarter cumulative excess return on corporate bonds. In Panel B, $\widehat{R}_{t\rightarrow t+k}$ is the predicted 4- or 8-quarter cumulative excess return on BAA-rated corporate bonds relative to AAA-rated bonds. In Panel C, $\widehat{R}_{t\rightarrow t+k}$ is the predicted 4- or 8-quarter cumulative excess bond premium by Gilchrist and Zakrajšek (2012). Robust t-statistics are shown in brackets.

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 6: Baseline 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%
$c_k = 0.658$	Adjustment cost	Mean investment rate
$\mu_z = 18.36$	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 (2003)
$\xi = 0.24$	Bankrupty cost	Mean default rate
$c = 0.0101$	Coupon rate	Price of default-free debt
$\lambda = 0.05$	Debt amortization rate	Average debt maturity
$c_e = 0.164$	Equity issuance cost	Mean leverage ratio
$B^{\max} = 0.69$	Maximum recovery rate	Top decile recovery rate
Learning		
ρ_s (see Table A.1)	Persistence of signal	Revision in expected profit
σ_u (see Table A.1)	Volatility of noise in signal	Revision 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 7.

Table 7: Model Fit

Panel A: Targeted moments	**Data** (1)	**Model** (2)
Investment rate (mean)	0.018	0.024
Leverage (mean)	0.267	0.309
Profit to asset (mean)	0.053	0.067
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	2.58
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. The data moments are calculated from the Compustat between 1985Q1 and 2010Q4.

Table 8: Model-Implied Forecasting Regressions

Panel A: Expected Corporate Profits and Credit Spreads

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

	1-qtr	2-qtr	3-qtr	4-qtr	8-qtr
β	-0.212	-0.175	-0.187	-0.146	-0.119
[t]	[-3.44]	[-2.58]	[-2.93]	[-3.35]	[-2.25]
R^2	0.19	0.10	0.11	0.15	0.06

Panel B: Expected Corporate Profits and Investment

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

	Inv 4-qtr	Inv 8-qtr		Output 4-qtr	Output 8-qtr
β	-0.836	-0.579		-0.143	-0.105
[t]	[-2.96]	[-2.63]		[-4.17]	[-2.38]
R^2	0.10	0.07		0.12	0.05

Note: This table presents the results of model-implied forecasting regressions. In Panel A, we regress the model-implied spread on investor expectations of corporate profits. The dependent variable $R_{t\rightarrow t+k}$ is the 1-,2-,3-,4-, or 8-quarter cumulative excess return on corporate bonds, respectively. The independent variable X_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 $BC_{t\rightarrow t+k}$ is the 4-, or 8-quarter ahead investment and output, respectively. The independent variable $\hat{R}_{t\rightarrow t+k}$ is the predicted 4- or 8-quarter cumulative excess return on corporate bonds, estimated from the forecasting regression in Panel A.

Table 9: Role of Information Frictions

	Data (1)	**With information frictions** (2)	**Without information frictions** (3)
First moments			
Default rate	0.013	0.010	0.011
Bond spread	0.019	0.017	0.009
Leverage	0.267	0.309	0.318
Investment	0.018	0.024	0.027
Second moments			
Corr(default, output)	−0.43	−0.17	0.35
Corr(spread, output)	−0.57	−0.31	0.47
Corr(invest, output)	0.57	0.74	0.68
σ(spread)/σ(output)	2.10	2.58	1.97
σ(invest)/σ(output)	3.46	2.75	2.36

Note: This table compares the model-generated moments in the model with and without information frictions. The difference between the two models lies in the bond pricing equation. In the baseline model with information frictions, the price of debt (given by equation (13) is a function of the public signal (s_t). In the model without information frictions, investors can observe the firm's state z_t after its realization so the price of debt is a function of z_t (see equation (A.1)).

Table 10: Role of Leverage and "Noisier" Signals

	Baseline	**Counterfactuals**		
	(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	0.010	0.007	0.020	0.024
Bond spread	0.017	0.031	0.046	0.028
Leverage	0.309	0.255	0.310	0.374
Investment	0.024	0.017	0.015	0.021
Second moments				
Corr(default, output)	−0.17	−0.22	−0.24	−0.15
Corr(spread, output)	−0.31	−0.26	−0.23	−0.28
Corr(invest, output)	0.74	0.63	0.66	0.68
σ(spread)/σ(output)	2.58	3.52	3.65	2.71
σ(invest)/σ(output)	2.75	2.96	3.11	2.86

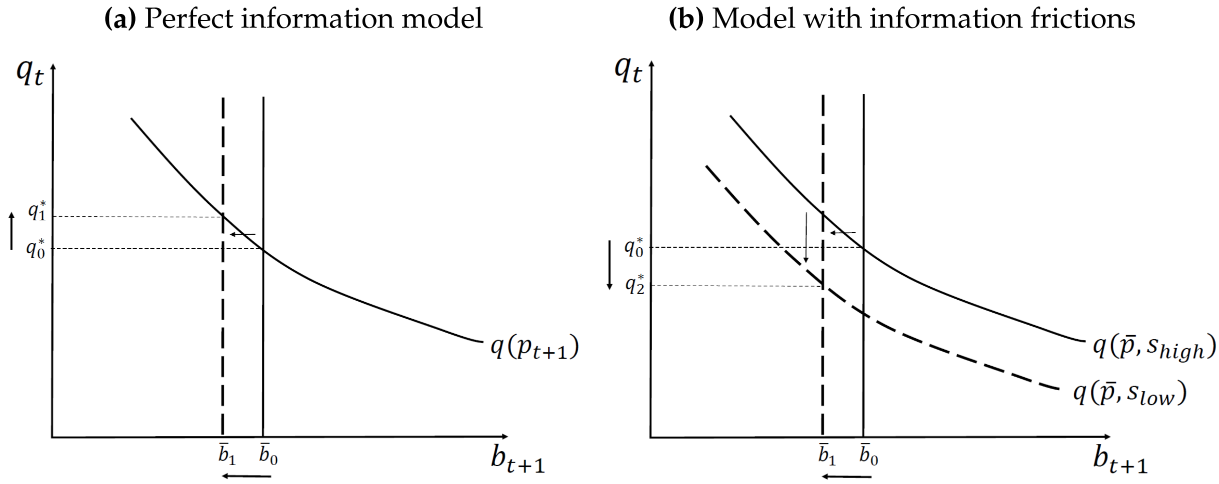
Note: This table compares the model predictions under different parameterization of σ_u (the volatility of noise) and c_e (the cost of equity financing) under rational learning. Column 1 presents the moments under the baseline calibration, as reported in Table 6. We consider three counterfactual models: (i) doubling σ_u (column 2); (ii) doubling both σ_u and c_e (column 3); (iii) doubling c_e (column 4).

Table 11: Aggregate Moments with Alternative Learning Rules

	Data	Baseline	Biased beliefs		Near rational		Overextrapolation	
			Pessimism	Optimism	$\omega = 0.1$	$\omega = 0.3$	$\zeta = 0.15$	$\zeta = 0.25$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
First moments								
Default rate	0.013	0.010	0.033	0.0036	0.009	0.012	0.015	0.021
Bond spread	0.019	0.017	0.0263	0.0057	0.016	0.020	0.028	0.042
Leverage	0.267	0.309	0.268	0.322	0.304	0.312	0.275	0.253
Investment	0.018	0.024	0.063	0.048	0.022	0.025	0.019	0.014
Second moments								
Corr(default, output)	−0.43	−0.17	−0.21	−0.09	−0.14	−0.07	−0.25	−0.31
Corr(spread, output)	−0.57	−0.31	−0.24	−0.16	−0.26	−0.14	−0.42	−0.48
Corr(invest, output)	0.57	0.74	0.66	0.61	0.66	0.56	0.77	0.82
σ(spread)/σ(output)	2.10	2.58	3.15	1.83	2.87	3.49	3.37	3.94
σ(invest)/σ(output)	3.46	2.75	3.26	2.15	3.04	3.37	2.92	3.15

Note: This table presents the aggregate moments in the alternative learning models with biased beliefs. 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, with $\zeta = 0.15$ and $\zeta = 0.25$, respectively. The models with pessimism and optimism are calibrated to match moments for speculative-grade and investment-grade firms, respectively (see Tables A.2 and A.3). The parameter values in the near rational and overextrapolation models are those reported in Table 6.

Figure 2: Comparing bond market equilibrium in models with and without information frictions



Note: This figure is a simplified illustration of the determination of bond prices during a technology-shock driven recession. In Panel (a), investors can perfectly observe the repayment probability p_{t+1}, which is decreasing in the level of borrowing b_{t+1}. The price of bond follows:

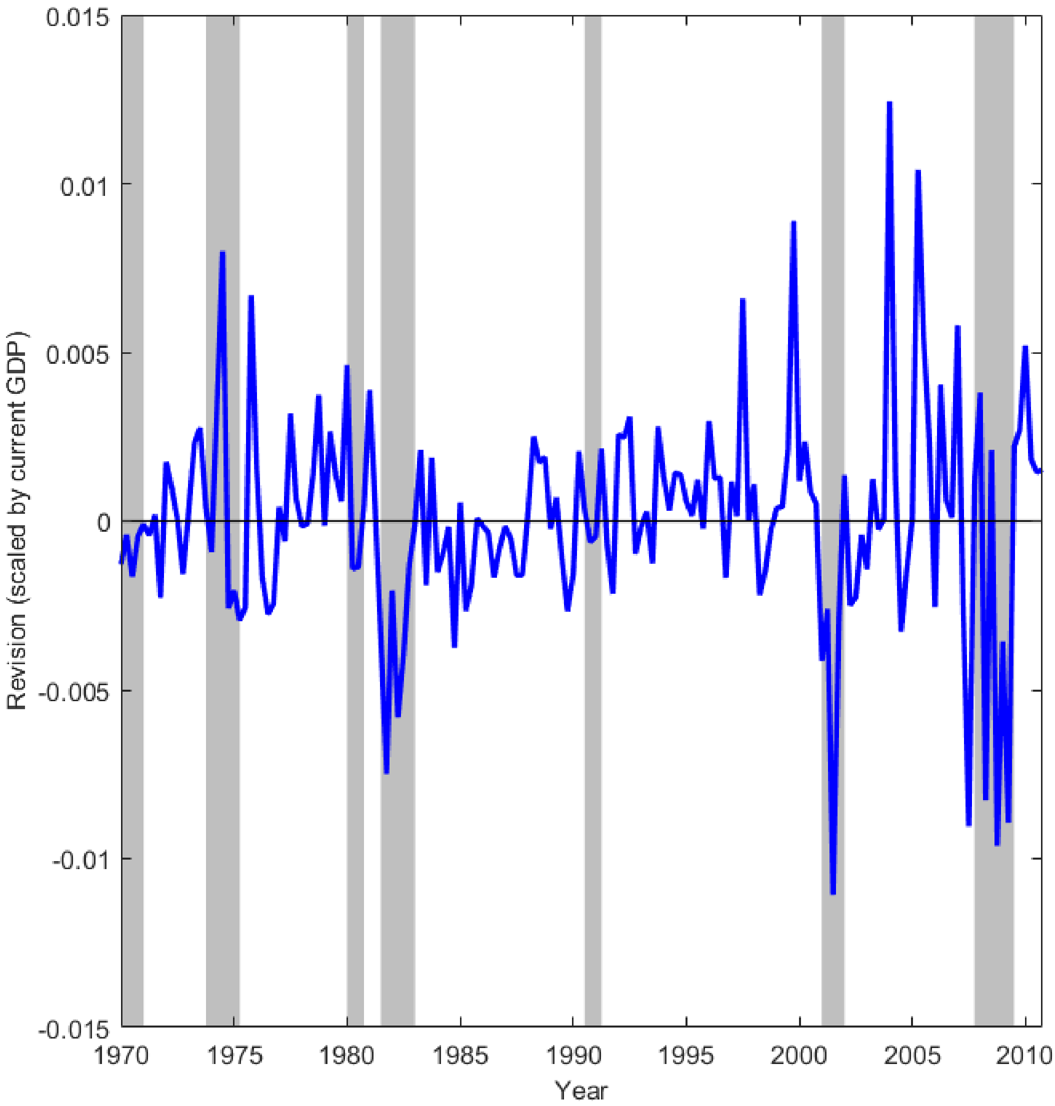
$$q_t = \beta\Big(\tilde{B} + (1 - \tilde{B})p_{t+1}\Big).$$

In a recession, the firm issues fewer bonds, so the supply curve shifts from $\bar{b}_0$ to $\bar{b}_1$. Panel (b) shows the additional impact of learning when investors cannot observe p_{t+1} and the price on bond is determined by:

$$q_t = \beta\left(\tilde{B} + \Big(1 - \tilde{B}\Big)\left[\bar{p} + \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_u^2} s_t\right]\right).$$

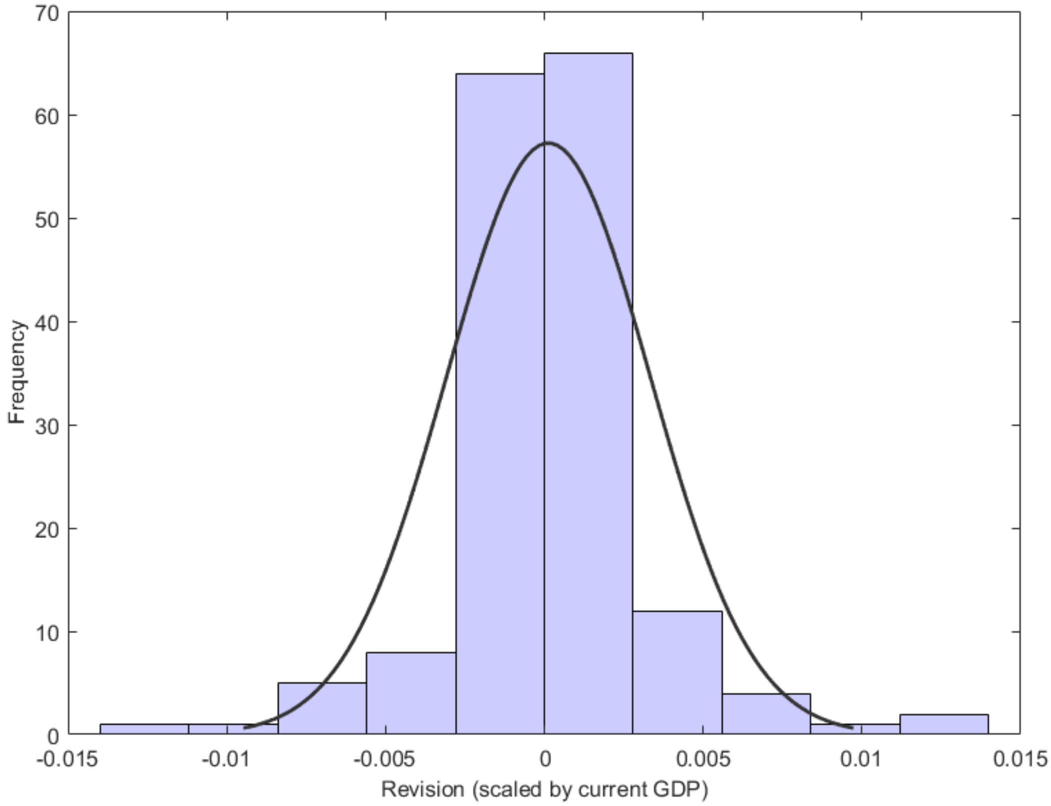
Therefore, in addition to the reduction of firm borrowing from $\bar{b}_0$ to $\bar{b}_1$, investors receive a more pessimistic signal about the firm's credit worthiness in a recession, so the demand curve shifts down from $q(\bar{p}, s_{\text{high}})$ to $q(\bar{p}, s_{\text{low}})$.

Figure 3: Current Revision in Investors' Expectations of Next Quarter Corporate Profits from the Survey of Professional Forecasters



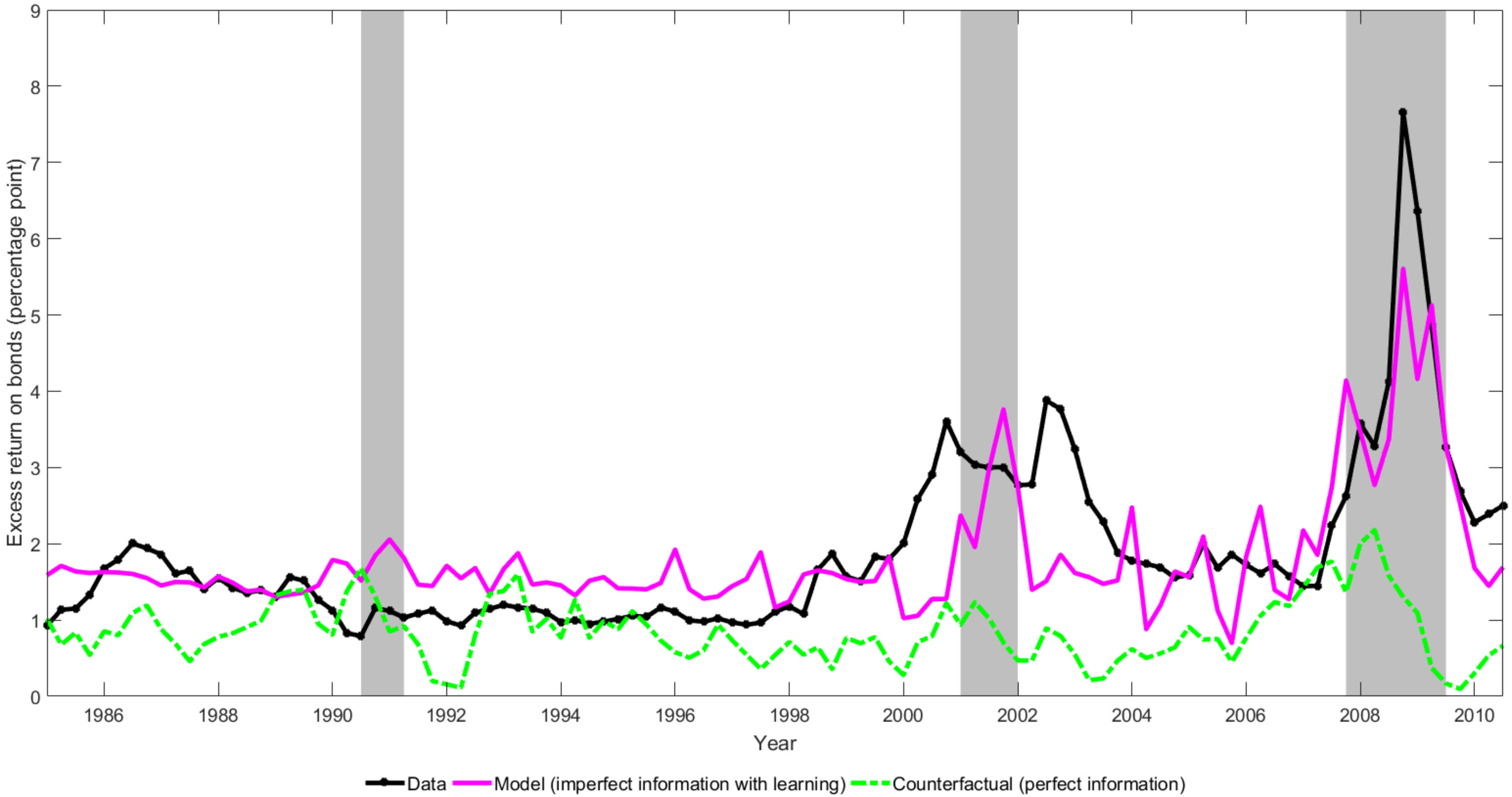
Note: This figure shows the current revision in investors' expectations of next quarter's corporate profit between 1970Q1 and 2010Q4, divided by the US GDP. Data is from the Survey of Professional Forecasters. Shaded areas indicate the NBER recession dates.

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 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 0.238.

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 1985Q1 and 2010Q4, comparing the data series (black line) and two different model-implied series: one from the imperfect information model with rational learning (purple line), and the other from the model without information frictions (green line). Shaded areas indicate the NBER recession dates.

The Expectations Driven Financial Accelerator
APPENDIX

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A Derivation of $\tilde{z}$ under rational learning

Define $\tilde{s}_t \equiv s_t - \rho_s s_{t-1}$, and equation (7) becomes:

$$\tilde{s}_t = -\varepsilon_{z,t} + u_t,$$

such that $(\tilde{s}_t,\ \varepsilon_{z,t}) \sim N\left[\begin{pmatrix}0\\0\end{pmatrix}, \begin{pmatrix}\sigma_\varepsilon^2+\sigma_u^2 & -\sigma_\varepsilon^2\\ -\sigma_\varepsilon^2 & \sigma_\varepsilon^2\end{pmatrix}\right]$, since u_t and $\varepsilon_{z,t}$ are i.i.d. normal. Then we have:

$$\mathrm{E}\Big(\varepsilon_{z,t}|s_t, s_{t-1}, ...s_0\Big) = \mathrm{E}\Big(\varepsilon_{z,t}|\tilde{s}_t\Big) = -\frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2+\sigma_u^2}\tilde{s}_t = -\frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2+\sigma_u^2}\big(s_t - \rho_s s_{t-1}\big).$$

From (5) we have:

$$z_t = \big(1-\rho_z L\big)^{-1}\big(\mu_z + \varepsilon_{z,t}\big)$$
$$\mathrm{E}\Big(z_t|s_t, s_{t-1}, ...s_0\Big) = \frac{\mu_z}{1-\rho_z} - \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2+\sigma_u^2}\sum_{j=0}^{\infty}\rho_z^j\big(s_{t-j} - \rho_s s_{t-j-1}\big),$$

which is equation (8).

B Computation

We transform (4) and (5) into discrete-state Markov chains using the method in Tauchen (1986). Investors know the distribution of z – including the range $[\underline{z}, \overline{z}]$ and transition function $P(z, dz')$ – but they cannot determine where the firm is on the z-grid.[14] Therefore, we distinguish between $P(z, dz')$ and $P(\tilde{z}, dz')$ in our notation, as $\tilde{z}$ may not coincide with z. We solve the model using value function iterations in the following steps:

1. Guess $q(k', b', \tilde{z}, a)$ and $V(k', b', z', a', \tilde{z}')$. Denote the initial guesses as $q_0(k', b', \tilde{z}, a)$ and $V_0(k', b', z', a', \tilde{z}')$;

2. Compute $J_0(k', b', z', a', \tilde{z}')$ using our guess $V_0(k', b', z', a', \tilde{z}')$, such that J_0 is bounded below at zero (10), and find the default "threshold" $z_0'^*(k', b', a', \tilde{z}')$;

3. Given $q_0(b', k', \tilde{z}, a)$, compute equity payout / dividend $e_0(k, b, z, a, \tilde{z}, b', k')$ using (12), and equity issuance cost $\Lambda\big(e_0(k, b, z, a, \tilde{z}, b', k')\big)$ using (6);

4. Given $q_0(b', k', \tilde{z}, a)$, $e_0(k, b, z, a, \tilde{z}, b', k')$, $\Lambda\big(e_0(b', k', b, k, a, z, \tilde{z})\big)$, $J_0(k', b', z', a', \tilde{z}')$, and the transition probabilities $P(z, dz')$, $P(\tilde{z}, d\tilde{z}')$ and $Q(a, da')$, find $V_0^*(k, b, z, a, \tilde{z})$ that satisfies the maximization problem (11) – subject to the default threshold (9) – and the policy functions $b_0'(k, b, z, a, \tilde{z})$ and $k_0'(k, b, z, a, \tilde{z})$;

5. Compute the right-hand side of the bond pricing equation (13):

   - Find $q_0(k'', b'', \tilde{z}', a')$ using our guess $q_0(k', b', \tilde{z}, a)$ as well as the policy functions from step 4 to determine b'' and k'';
   - Use $V_0(k', b', z', a', \tilde{z}')$ and $q_0(k'', b'', \tilde{z}', a')$ to obtain $\tilde{B}_0(k', b', z', a', \tilde{z}')$ according to (14);
   - Compute the expected values using the default threshold $z_0'^*(k', b', a', \tilde{z}')$ from step 2, and the transition probabilities $P(z, dz')$, $P(\tilde{z}, d\tilde{z}')$ and $Q(a, da')$;

6. Updating:

   - Update $V_1(k', b', z', a', \tilde{z}') = V_0^*(k, b, z, a, \tilde{z})$;

[14] In our simulation for the period 1985Q1-2010Q4, we use an expanding window to find the values for ρ_s and σ_u (see Appendix A.1). We use them to obtain the series for $\tilde{z}$ as specified in (8). Each value of $\tilde{z}$ is matched to the closest value on the z-grid.

- Compare $q_0(b',k',\tilde{z},a)$ and the right-hand side of the bond pricing equation from step 5. If the difference is greater than $\varepsilon \approx 0$, use bisection method to update our guess to $q_1(b',k',\tilde{z},a)$;

7. Repeat steps 2–6 until convergence, i.e. the following conditions

$$|q_{T+1}(k',b',\tilde{z},a) - q_T(k',b',\tilde{z},a)| < \varepsilon$$
$$|V_{T+1}(b',k',z',a',\tilde{z}') - V_T(b',k',z',a',\tilde{z}')| < \varepsilon$$

are jointly satisfied, for $\varepsilon \approx 0$.

C Model with Perfect Information

If investors can observe z, then the price of bond q is a function of z instead of $\tilde{z}$:

$$q(b',k',z,a) = \beta \left\{ \int_{\underline{a}}^{\overline{a}} \int_{\underline{z}}^{z^*(k',b',a')} \Big[c + \lambda + (1-\lambda) q'(b'',k'',z',a')\Big] P(z,dz') Q(a,da') \right.$$
$$\left. + \int_{\underline{a}}^{\overline{a}} \int_{z^*(k',b',a')}^{\overline{z}} B(b',k',z',a') \;\; P(z,dz') Q(a,da') \right\}, \tag{A.1}$$

and the default threshold $z^*(k',b',a')$ is pinned down by the condition:

$$J(k',b',z^*,a') = 0.$$

As before, $B(b',k',z',a')$ is the recuperation rate of bond that takes the value between 0 and the maximum recovery rate $B_{\max}$:

$$B(b',k',z',a') = \min \Bigg[\max \Big[0, \; \Big((1-\tau)\big(a' k'^{\alpha} - z'\big) + V(k',b',z',a')$$
$$+ (1-\lambda) q'(b'',k'',z',a') b' - \xi k' \Big) \frac{1}{b'} \Big], \;\; B^{\max} \Bigg]. \tag{A.2}$$

Since q is no longer a function of $\tilde{z}$, there is one fewer state in the firm's problem, compared to the imperfect information model. The equity value of the firm is:

$$J(k,b,z,a) = \max \Bigg[0, \; (1-\tau)\big(ak^{\alpha} - z\big) - \big(c+\lambda\big) b + \tau\big(\delta k + cb\big) + V(k,b,z,a) \Bigg], \tag{A.3}$$

where

$$V(k,b,z,a) = \max_{b',k',e} \left\{ q\Big(b' - (1-\lambda) b\Big) - \Big(k' - (1-\delta) k\Big) - g(k,k') + \Lambda(e) \right.$$
$$\left. + \beta \int_{\underline{a}}^{\overline{a}} \int_{\underline{z}}^{z^*(k',b',a')} J\big(k',b',z',A'\big) \;\; P(z,dz') Q(a,da') \right\}, \tag{A.4}$$

subject to (6), (9), and the definition of equity payout / issuance:

$$e = (1-\tau)\big(ak^{\alpha} - z\big) - \big(c+\lambda\big) b - \big(k' - (1-\delta) k\big) - g\big(k,k'\big) + \tau\big(\delta k + cb\big)$$
$$+ q(b',k',z,a)\Big(b' - (1-\lambda) b\Big).$$

D Additional Tables and Figures

Table A.1: Calibration of the Learning Parameters σ_s and σ_u

Year	Quarter	ρ_s	σ_u	Year	Quarter	ρ_s	σ_u
1985	1	0.2619	0.0479	1998	1	0.2487	0.0431
1985	2	0.2559	0.0483	1998	2	0.2461	0.0431
1985	3	0.2694	0.0479	1998	3	0.2482	0.0428
1985	4	0.2647	0.0475	1998	4	0.2480	0.0425
1986	1	0.2646	0.0470	1999	1	0.2479	0.0423
1986	2	0.2648	0.0465	1999	2	0.2480	0.0420
1986	3	0.2672	0.0463	1999	3	0.2490	0.0419
1986	4	0.2700	0.0458	1999	4	0.2678	0.0436
1987	1	0.2697	0.0453	2000	1	0.2573	0.0435
1987	2	0.2701	0.0449	2000	2	0.2591	0.0434
1987	3	0.2741	0.0447	2000	3	0.2595	0.0431
1987	4	0.2845	0.0444	2000	4	0.2597	0.0428
1988	1	0.2782	0.0441	2001	1	0.2581	0.0430
1988	2	0.2815	0.0449	2001	2	0.2630	0.0429
1988	3	0.2941	0.0448	2001	3	0.2899	0.0467
1988	4	0.3048	0.0447	2001	4	0.2878	0.0468
1989	1	0.2983	0.0444	2002	1	0.2804	0.0467
1989	2	0.2975	0.0441	2002	2	0.2758	0.0468
1989	3	0.2936	0.0439	2002	3	0.2805	0.0466
1989	4	0.3059	0.0443	2002	4	0.2799	0.0464
1990	1	0.3178	0.0440	2003	1	0.2805	0.0462
1990	2	0.2945	0.0450	2003	2	0.2777	0.0461
1990	3	0.2915	0.0447	2003	3	0.2768	0.0459
1990	4	0.2902	0.0444	2003	4	0.2768	0.0456
1991	1	0.2911	0.0440	2004	1	0.2778	0.0501
1991	2	0.2856	0.0446	2004	2	0.2518	0.0504
1991	3	0.2726	0.0445	2004	3	0.2492	0.0504
1991	4	0.2786	0.0446	2004	4	0.2502	0.0502
1992	1	0.2486	0.0458	2005	1	0.2499	0.0500
1992	2	0.2655	0.0458	2005	2	0.2504	0.0515
1992	3	0.2826	0.0460	2005	3	0.2592	0.0514
1992	4	0.2684	0.0460	2005	4	0.2608	0.0512
1993	1	0.2682	0.0456	2006	1	0.2586	0.0511
1993	2	0.2681	0.0453	2006	2	0.2551	0.0511
1993	3	0.2672	0.0451	2006	3	0.2546	0.0508
1993	4	0.2587	0.0455	2006	4	0.2545	0.0506
1994	1	0.2618	0.0452	2007	1	0.2547	0.0506
1994	2	0.2617	0.0449	2007	2	0.2490	0.0506
1994	3	0.2625	0.0446	2007	3	0.2539	0.0509

1994	4	0.2649	0.0444	2007	4	0.2469	0.0508
1995	1	0.2654	0.0441	2008	1	0.2480	0.0507
1995	2	0.2655	0.0438	2008	2	0.2396	0.0511
1995	3	0.2658	0.0435	2008	3	0.2317	0.0511
1995	4	0.2647	0.0432	2008	4	0.2262	0.0517
1996	1	0.2637	0.0434	2009	1	0.2308	0.0516
1996	2	0.2655	0.0431	2009	2	0.2398	0.0520
1996	3	0.2671	0.0428	2009	3	0.2274	0.0521
1996	4	0.2637	0.0427	2009	4	0.2291	0.0519
1997	1	0.2603	0.0425	2010	1	0.2330	0.0519
1997	2	0.2601	0.0422	2010	2	0.2338	0.0517
1997	3	0.2613	0.0435	2010	3	0.2343	0.0515
1997	4	0.2487	0.0434	2010	4	0.2347	0.0513

Note: This table reports the persistence of the signal ρ_s and the volatility of its noise σ_u used in the quantitative model. We first compute the percentage change in forecasters' expectations of the quarter-ahead corporate profits, i.e. $s_t = \ln \mathrm{E}_t(\Pi_{t+1}) - \ln \mathrm{E}_{t-1}(\Pi_{t+1})$, and estimate an AR(1) process:

$$s_t = \rho_s s_{t-1} + \eta_t$$

using an expanding window: for each quarter, we estimate ρ_s using all the data points from the revision series starting from 1971Q1 up to the current period. We obtain σ_s in a similar way, and the volatility of noise σ_u is derived from the relation: $\sigma_u^2 = (1-\rho_s^2)\sigma_s^2 - \sigma_\varepsilon^2$.

Table A.2: Parameterization in Model with Pessimistic Beliefs

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%
$c_k = 0.327$	Adjustment cost	Mean investment rate
$\mu_z = 16.23$	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 (2003)
$\xi = 0.1$	Bankrupty cost	Hennessy and Whited (2007)
$c = 0.0101$	Coupon rate	Price of default-free debt
$\lambda = 0.05$	Debt amortization rate	Average debt maturity
$c_e = 0.117$	Equity issuance cost	Mean leverage ratio
$B^{\max} = 0.69$	Maximum recovery rate	Top decile recovery rate
Learning		
ρ_s (see Table A.1)	Persistence of signal	Revision in expected profit
σ_u (see Table A.1)	Volatility of noise in signal	Revision in expected profit
$\psi_p = 3.92$	Pessimism	Default rate (high yield)

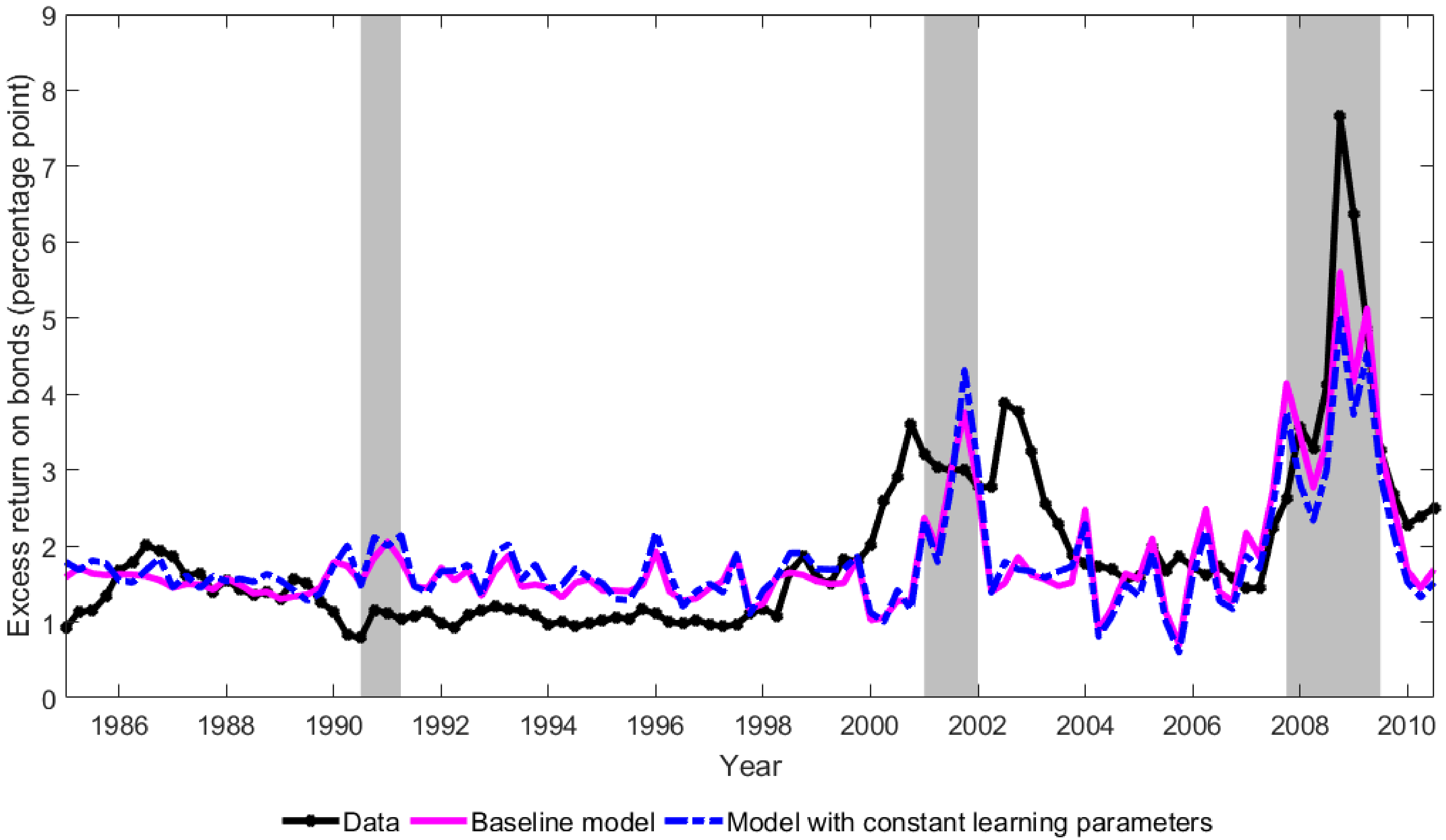
Note: This table presents the calibrated parameters in the alternative learning model with "pessimistic" investors. The model is calibrated to match the following moments for firms issuing high-yield bonds: mean investment rate, mean profit-to-asset, mean leverage ratio, and mean default rate.

Table A.3: Parameterization in Model with Optimistic Beliefs

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%
$c_k = 0.318$	Adjustment cost	Mean investment rate
$\mu_z = 15.13$	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 (2003)
$\xi = 0.1$	Bankrupty cost	Hennessy and Whited (2007)
$c = 0.0101$	Coupon rate	Price of default-free debt
$\lambda = 0.05$	Debt amortization rate	Average debt maturity
$c_e = 0.152$	Equity issuance cost	Mean leverage ratio
$B^{\max} = 0.69$	Maximum recovery rate	Top decile for corporate bonds
Learning		
ρ_s (see Table A.1)	Persistence of signal	Revision in expected profit
σ_u (see Table A.1)	Volatility of noise in signal	Revision in expected profit
$\psi_o = -2.47$	Optimism	Default rate (investment grade)

Note: This table presents the calibrated parameters in the alternative learning model with "optimistic" investors. The model is calibrated to match the following moments for firms issuing investment-grade bonds: mean investment rate, mean profit-to-asset, mean leverage ratio, and mean default rate.

Figure A.1: Robustness Check: Constant Learning Parameters (σ_u, ρ_s)



Note: This figure shows the time series of corporate bond spread in the US between 1985Q1 and 2010Q4 in the data (black line) and two versions of the model with rational learning. In our baseline model (purple line), investors learn about (σ_u, ρ_s) over time (see Table A.1). As a robustness check (blue line), we use the estimated values from the whole sample (1985Q1-2010Q4), yielding $\sigma_u = 0.048$ and $\rho_s = 0.264$. Shaded areas indicate the NBER recession dates.