The Expectations Driven Financial Accelerator*

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December 12, 2019

Abstract

This paper argues that imperfect information in credit markets is a source of macroeconomic fragility. Using a dynamic model with endogenous default, we highlight a novel mechanism whereby uninformed debt investors learn about firms' creditworthiness from publicly-available information on quarter-ahead corporate profits. We show that: 1) short-term changes in expectations of corporate profits forecast credit spreads and investment up to two years ahead both in the aggregate and at the firm level; 2) spreads and defaults are counter-cyclical; 3) the mechanism can account quantitatively for the historically large spike in spreads and contraction in aggregate investment during the crisis.

JEL codes: D84, G12, G30, E32

Keywords: expectations, learning, credit market volatility, business cycles

*For helpful comments and suggestions, we thank Joao Gomes, Yuriy Gorodnichenko, Robin Greenwood, Joe Kaboski, Albert Marcet, Stefan Nagel, Bruce Preston, Eric Sims, and conference participants at Econometrics Society Meetings, Expectations in Dynamic Macroeconomic Models Workshop, Oxford-NY Fed-BoE Monetary Economics Conference, and Bank of Finland-CEPR Joint Conference on Monetary Economics and Reality. We are also grateful to Sushant Acharya and Egon Zakrajšek for their insightful discussions. The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Board of Governors or the Federal Reserve System. Correspondence: antonio.falato@frb.gov; jasmine.xiao@nd.edu.

1 Introduction

That investors in financial markets make decisions with limited, and often far from perfect, information available to guide them has long been known in financial economics going as far back as Keynes (1936), and has been recognized in classic accounts of financial crises by Minsky (1977, 1986) and Kindleberger (1978). Yet whether information frictions played a role in recent episodes of dramatic credit market volatility has received surprisingly little attention. This gap in the literature on financial market conditions and the macroeconomy[1] raises two important questions: What drives cyclical volatility in credit markets, and is there a role for imperfect information? If so, does imperfect information in credit markets matter, in turn, for the cyclical volatility of the real economy?

We propose a theory of macro fragility based on imperfect information and learning in credit markets. Episodes of drastic volatility in credit markets that lead to aggregate contractions in economic activity are challenging to explain from the standpoint of efficient debt markets under perfect information. Yet these and other critical features of the credit cycle fit naturally within our theory. To formalize the intuition, we embed learning by uninformed debt investors into a standard dynamic macro-finance setting with financial frictions and endogenous default (e.g., Gomes and Schmid, 2017). The mechanism is that debt investors form beliefs about firms' creditworthiness using publicly-available information on quarter-ahead corporate profits from professional forecasters. When the short-term profit outlook deteriorates, they become pessimistic about firm default risk. In turn, firm insiders perceive that debt is underpriced and cut back investment.

Using a calibration of the model to gauge the quantitative importance of this learning mechanism, we highlight the following results. First, we show that realistic episodes of heightened credit market volatility can originate from credit-market investors' learning from noisy public information. The model generates counter-cyclical spreads, in line with the data but in sharp contrast to the counterfactually pro-cyclical spreads under perfect information. And it predicts a spike in spreads that is about two-thirds as large as its empirical counterpart in the crisis. Second, the mechanism generates credit cycles that lead to macro fragility. Credit spreads and aggregate investment are jointly predictable over long horizons using short-term changes in professional forecasts of corporate profits, in line with the data. And negative revisions to the short-term profit outlook account for about a quarter of the contraction in aggregate investment during the crisis.

Finally, the unique mechanism at the core of our model is testable and we find strong support for it using analyst forecast data from I/B/E/S to measure changes in expectations at the firm level: (1) there is a negative (positive) relation between short-term

[1] See Gertler and Gilchrist (2018) for a recent survey.

changes in expectations of corporate profits and corporate debt spreads (investment) over long horizons; (2) the relation remains strong even after we refine identification by isolating exogenous variation or "shocks" to expectations that are plausibly unrelated to macroeconomic and firm fundamentals with two different identification strategies; (3) aggregate counterfactual and sample-split analyses support the central implication of the model that fluctuations in expectations are a source of macro fragility. In all, we conclude that informational inefficiencies in debt markets help to explain critical features of credit cycles and provide a novel mechanism through which credit market fluctuations lead to macroeconomic fragility.

We begin by documenting new stylized facts on the time-series link between changes in expectations of corporate profits, credits spreads, and macroeconomic aggregates. First, a measure of changes in professional forecasters' expectations of quarter-ahead corporate profits is a strong time-series 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 measures of expected risk premiums in the corporate bond market, including the excess return on corporate bonds, over up to 2 years horizons. In turn, by inducing time-variation in expected returns to credit market investors, short-term changes in expectations lead to aggregate fluctuations on the real side of the economy: short-term changes in investor expectations of corporate profits have significant forecasting power for economic aggregates including GDP growth and business investment over up to 2 years horizons. As such, our stylized facts indicate 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. The joint predictability of bond returns and macroeconomic aggregates motivates our modelling choices for credit-market investors' learning.

Next, to better understand the economic mechanism behind the stylized facts and its implications, we build a tractable quantitative model of firm financing and investment. We introduce learning by uninformed debt-market investors into an otherwise standard dynamic setup with endogenous default (Hennessy and Whited, 2007, 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 learning from publicly-available information – i.e., using information on quarter-ahead corporate profits from professional forecasters; second, credit-market investors' beliefs about firm creditworthiness affect debt pricing and, thus, firm leverage and investment decisions. By introducing learning into a unified framework with debt pricing, investment, and production, we are able to highlight and quantify the learning mechanism behind the link between changes in expectations and financial and real outcomes.

For a realistic parametrization that is calibrated to match average investment, leverage, profitability, and default rates, we show the following main results. First, the model successfully replicates the stylized facts – 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. Second, 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. Third, 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 about two thirds of the overall spike episode. And about a quarter of the contraction in aggregate investment during the crisis can be attributed to negative revisions of the profit outlook. These results are not sensitive to the details of our baseline modeling choices, and continue to hold after we allow for deviations from rational learning or for a general equilibrium extension.[2] Overall, our theory provides a novel explanation for why credit market volatility can lead to macroeconomic fragility based on information frictions and learning.

Finally, the model has unique testable implications, which offer an opportunity to probe the plausibility of the mechanism using micro data. These predictions include that there should be a negative (positive) relation between changes in expectations of corporate profits and corporate debt spreads (investment), for which we find support also in a large cross-section of firms. A firm-level measure of short-term quarterly analyst forecast revisions between 1982 and 2010 from I/B/E/S is strongly economically related to spreads and investment over long horizons. Importantly, the relation remains strong even after we refine identification by isolating exogenous variation in revisions or

[2]The model results continue to hold also in the more special case when debt is the only type of external financing (i.e., if we do not allowing for outside equity issuance).

"shocks" to expectations that are plausibly unrelated to macroeconomic and firm fundamentals. We construct the expectations shocks using two identification strategies. The first is to construct the shocks similar to Fracassi, Petry, and Tate (2016), using analyst–specific changes in expectations that are orthogonal to firm fundamentals.

The second is to use a quasi-natural experiment that exploits plausibly exogenous variation in revisions around brokerage house mergers. The source of identification here is that, as documented by Hong and Kacperczyk (2010), these mergers reduce competition and lead to an increase in optimism bias for firms covered by both merging houses before the merger – i.e., they have a positive effect on revisions, which is plausibly unrelated to firm fundamentals. This analysis helps to distinguish our mechanism from other macro theories because it shows that changes in expectations matter for spreads and investment, suggesting that the direction of causality is from expectations to aggregate outcomes. As such, the evidence also helps to distinguish from behavioral theories that emphasize diagnostic expectations (e.g., Bordalo, Gennaioli, and Shleifer, 2018, Bordalo, Gennaioli, Shleifer, and Terry, 2019), because in these theories changes in fundamentals remain the only driving force. Finally, additional evidence from an aggregate counterfactual confirms that the mechanism can account for about a quarter of the aggregate contraction in investment during the crisis. Sample-split analysis further supports the central implication of the model that fluctuations in expectations are a source of macro fragility.

Our paper makes two main contributions. First, we contribute to the macro-finance literature on models of business cycle volatility with a financial sector (see Gertler and Gilchrist, 2018 for a recent survey) by highlighting a novel source of macro fragility, imperfect information and learning in credit markets.[3] As in standard models of the financial accelerator (e.g. Bernanke, Gertler, and Gilchrist, 1999, Kiyotaki and Moore, 1997, and Carlstrom and Fuerst, 1997), in our theory the amplification mechanism for aggregate fluctuations operates via endogenous movements in asset prices. The main innovation is that changes in expectations, rather than just changes in fundamentals, are the drivers of movements in asset prices, which highlights the interplay between financial and information frictions on the real economy. The broader implication that there is a strong link between fluctuations in credit markets and macroeconomic cycles is supported by the influential evidence that risk premiums in credit markets are predictable and closely tied

[3]So far this literature has emphasized the role of leverage and weak balance sheets as sources of macro fragility, with a focus on the balance sheet of either firms (Bernanke, Gertler, and Gilchrist, 1999, and Kiyotaki and Moore, 1997), households (Mian, Rao, and Sufi, 2013, and Guerrieri and Lorenzoni, 2017), or intermediaries (He and Krishnamurthy, 2013, and Brunnermeier and Sannikov, 2014). Even before the crisis, bond markets have become a significant source of financing for U.S. firms (see, for example, Benmelech, Kumar, and Rajan, 2019), highlighting the importance to better understand their connection with the macroeconomy.

to future movements in economic activity (Greenwood and Hanson, 2013, and López-Salido, Stein, and Zakrajšek, 2017). As such, we also contribute a novel mechanism to the finance literature on the real effects of financial markets (see Bond, Edmans, and Goldstein, 2012 for a survey), which has focused primarily on equity markets.

Second, we contribute to the recent growing literature on expectations and learning in finance and macroeconomics.[4] The most closely related papers are Adam, Marcet, and Nicolini (2016) and Adam, Marcet, and Beutel (2017), who show that subjective expectations and rational learning can generate realistic amounts of volatility and boom-bust cycles in stock prices. Nagel and Xu (2019) study the equity premium in an economy in which agents learn with fading memory, and show that subjective belief dynamics generate predictable variation in the equity premium. We focus on debt rather than equity markets, but share a common theme with these papers – that investors' beliefs about fundamentals differ from objective beliefs. Investors in our model learn from exogenous public signals, instead of prices. As these public signals may not coincide with firm fundamentals, there is a wedge between the beliefs of insiders (firm) and outsiders. And, because signals are noisy, new information gets incorporated slowly into debt prices through investors' belief updating. Our contribution is to show that learning is relevant beyond just equity markets and to provide a mechanism that leads to predictability and macro fragility even in the rational learning benchmark.[5]

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 provides further supporting evidence of the mechanism from micro-level data. Section 7 shows that our model predictions are robust in a general equilibrium setting. Section 8 concludes.

[4]This literature so far has also examined various other deviations from rational learning, including biased beliefs (Alti and Tetlock, 2013), sticky expectations (Bouchaud, Kruger, Landier, and Thesmar, 2019, and Coibion and Gorodnichenko, 2015), diagnostic and extrapolative expectations (Landier, Ma, and Thesmar, 2019, Weber, 2018, Bordalo, Gennaioli, and Shleifer, 2018, Bordalo, Gennaioli, Shleifer, and Terry, 2019, and Greenwood, Hanson, and Jin, 2019), and expectations errors (Ma, Ropele, Sraer, and Thesmar, 2019).

[5]The result echoes some of the themes from the classical literature on learning and herding in finance (Scharfstein and Stein, 1990, Froot, Scharfstein, and Stein, 1992, and Bikhchandani, Hirshleifer, and Welch, 1992). 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. Though obtained in a very different context, our result that rational learning can lead to myopia parallels that of Stein (1989).

2 Stylized Facts

The central premise of our theory is that changes in investor expectations drive risk premiums in debt markets and that, in turn, by inducing time-variation in cost of debt financing, they lead to aggregate fluctuations on the real side of the economy. In this section, we construct a measure of changes in investor expectations and use macro data to document new stylized facts on the time-series relation between investor expectations, credit spreads, and macroeconomic aggregates.

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

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

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

where $R_{t,t+k}$ is the k-quarter cumulative excess return, with $k = 1,2,4,8$ respectively. X_t is our explanatory variable of interest – that is, either the measure of expectations of corporate profits Rev_t, or its dispersion σ_t - in each quarter. Controls include aggregate indicators of macroeconomic conditions (aggregate consumption, business investment, GDP, and corporate profitability (ROA)), excess stock returns, short and long rates (1-year Treasuries and the effective Fed Fund Rate), the term spread, and lagged excess returns. We compute the t-statistics for k-period forecasting regressions based on Newey and West (1987) standard errors, allowing for serial correlation up to $k-1$ lags.

We report the main results in Panel A, where we measure expected risk premiums in the corporate bond market using the excess return on corporate bonds. In Panel B, we show robustness to adding controls for other predictors that have been established in the literature, which include growth in aggregate total factor productivity (Bordalo, Gennaioli, and Shleifer, 2018; Bordalo, Gennaioli, Shleifer, and Terry, 2019), the high-yield share of new bond issues (Greenwood and Hanson, 2013), the lagged corporate bond premium (López-Salido, Stein, and Zakrajšek, 2017), and a measure of equity market sentiment from Baker and Wurgler (2006).[6]

Since the measures of expectations are scaled by their respective unconditional standard deviation, we can interpret the coefficients in Table 2 as the change in excess return (in percentage point) associated with a one standard deviation revision in expectations Rev_t, or its noise σ_t. For instance, Panel A of Table 2 reports that a one standard deviation upward revision in investors' expectations lowers the excess return on corporate bonds by about 14 basis points in the following quarter, whereas a one standard deviation increase in the dispersion of revisions raises the spreads by about 24 basis points, which are respectively about 10 percent and 15 percent of the unconditional mean of spreads in our sample (1.6 percentage points). 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 about 80 basis points ($0.143\times0.44+0.242\times3$), 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 Table 3, we show that our survey-based measure of changes in investor expectations of aggregate corporate profits has significant forecasting power for various standard economic aggregates, including GDP growth and business investment. In Appendix Table A.2, we show results for additional aggregate outcomes, which include aggregate

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

consumption and employment growth. We run multivariate time-series forecasting regressions of business cycle aggregates on the component of excess bond returns that is predictable based on investor expectations of corporate profits, controlling for macroeconomic conditions, excess stock returns, short and long rates, and the term spread:

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

where $BC_{t\rightarrow t+k}$ is the business cycle variable k quarters ahead, with $k = 4, 8$ respectively. $\widehat{R}_{t\rightarrow t+k}$ is the predicted 4- or 8-quarter cumulative excess return on corporate bonds, estimated from the multivariate forecasting regression of credit spreads using either our measure of expectations of corporate profits Rev_t or its dispersion σ_t in each quarter. As in the earlier regressions, besides the excess return on corporate bonds (Panel A), we also consider the predicted 4- or 8-quarter cumulative excess return on BAA-rated corporate bonds relative to AAA-rated bonds (Panel B), and the predicted 4- or 8-quarter cumulative excess bond premium by Gilchrist and Zakrajšek (2012).

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

The combined magnitudes of the first stage estimates in Table 2 and the second stage estimates in Table 3 indicate that the key mechanism at the core of our model is economically meaningful also on the real side. The unconditional mean quarterly growth rates of investment and GDP in our sample are about 1 percentage point and 70 basis points, respectively. For example, the combined estimates in Tables 2 and 3 imply that a one-standard deviation shock to revisions shaves off about 10 percent of the quarterly mean growth rate of investment, which corresponds to about 40 basis points of investment growth on an annual basis. Considering again the 2006 to 2008 period, our estimates imply that the combined effect of downward revisions and higher dispersion lowered investment by almost 1 percentage point ($-1.46\times -0.064\times 0.44 - 0.843\times -0.343\times 3$) and GDP by about 40 basis points ($-0.277\times -0.064\times 0.44 - 0.338\times -0.343\times 3$), 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 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 learning from noisy signals can affect corporate bond pricing and, thus, firm leverage and investment decisions.[7]

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

[7]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.

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:

$$\log a' = \rho_a \log a + \varepsilon_a' \tag{3}$$

$$z' = \mu_z + \rho_z z + \varepsilon_z', \tag{4}$$

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:

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

subject to a quadratic investment adjustment cost:

$$g(k, k') = \frac{c_k}{2}\left(\frac{k' - (1-\delta)k}{k}\right)^2 k. \tag{5}$$

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. Following Gomes and Schmid (2017), we adopt a reduced-form approach by choosing a proportional equity issuance cost:

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

where $1_{e<0}$ is an indicator variable that equals to 1 if $e < 0$ and 0 otherwise.[8]

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 (4), 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:[9]

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

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 (4) and s (7) to form an estimate of z (denoted by $\tilde{z}$) using the following relation:

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

given the history of s up to the current period, $\mathcal{S} = \left\{s_0, s_1, ..., s\right\}$. 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

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

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

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[8] We also solve a version of the model without equity financing, whereby the firm faces a non-negative dividend constraint in each period, and can only tap into the debt markets to raise external finance. The results are presented in Table A.8 in the appendix.

[9] We use this process to fit the data (see Section 5). Our main results continue to hold even if the signals were iid ($\rho_s = 0$). For instance, the predictability of (model-implied) spread from the current signal does not depend on $\rho_s > 0$ if the fundamental z follows a persistent process with $\rho_z > 0$.

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):

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

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

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

The definition of equity payout / issuance is given by:

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

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 below. 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, $(c+\lambda)b$. 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

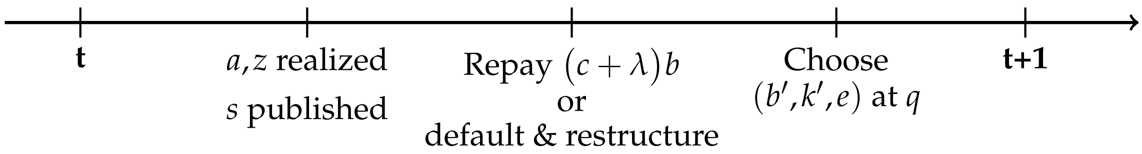

Figure 1: Timing of the firm's problem

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:[10]

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

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:

[10] 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).

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 optimization 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:

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

If the investors are risk-neutral, the spread between the risky bond and the risk-free bond is given by:[11]

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

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}:

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

[11]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 (such as in our dynamic model in Section 3), 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 and endogenous default, 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.[12] Quantitatively, which force dominates is ambiguous, and depends on how

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

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 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

our model, the mechanism is embedded in the pricing of debt by investors and incomplete markets play a crucial role.

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. $s_t = \ln \mathrm{E}_t(\Pi_{t+1}) - \ln \mathrm{E}_{t-1}(\Pi_{t+1})$.[13] 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, 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

[13]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.

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 4. In addition, Table A.3 reports the empirical estimates of ρ_s and σ_u for each quarter between 1985Q1 and 2010Q4.

5.2 Model Fit

Table 5 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 asymmetric 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 forecasting regression 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 6. 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

Columns (2) and (3) of Table 5 compare the moments generated from the asymmetric information model with those from a counterfactual model in which bond investors have the same information set as the firm.[14] We show that informational inefficiencies in the

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

debt markets have three main effects on corporate bond spreads.

First, spreads are significantly lower in the full 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. In our baseline model, however, because investors are uncertain about a low probability event such as firm default, they demand higher premia.[15] While this mechanism is absent in standard firm financing models with only financial frictions, it allows our 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 full 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, σ_u and ρ_s over time.[16]

Third, without information frictions, credit spreads are procyclical in a technology-driven business cycle model with costly external finance and endogenous default, 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 5, both spreads and default rates are procyclical in the counterfactual model with full information. By contrast, the asymmetric 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. The signal effect quantitatively domi-

[15]This result comes from Jensen's inequality. For illustration, since investors do not observe z, their estimate of the firm's default probability $\Omega(\cdot)$ is a function of $\tilde{z}$ instead of z. With $\tilde{z} = z + u$ and $\mathrm{E}(u) = 0$, $\mathrm{E}(\Omega(\tilde{z})) > \mathrm{E}(\Omega(z))$, since in our model $\Omega(\cdot)$ is a nonlinear function of z and default is a low probability event.

[16]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.2. As shown in Table A.3, 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.

nates the leverage effect on the equilibrium price of debt, because the signals are not only procyclical, but also more volatile in crisis (see Figure 3).[17]

Economic significance of noisy signals To understand the economic significance of learning from "noisy" signals, especially during the 2007-09 financial crisis, we conduct the following counterfactual experiment. We continue to assume that there is asymmetric information between debt investors and the firm, and that investors learn from public signals, but we replace the original signals with the pre-crisis average for the crisis period. Subsequently, we compute the average spread and annualized change in investment during the crisis, and compare them to their counterparts in the baseline model. As shown in Panel C of Table 5, in an economy without noisy signals, the model-implied (average) spread would be around 2 percentage points lower during the crisis, and the contraction in investment would be 23 percent less.[18]

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 7 compares the aggregate moments in our baseline model (low noise-low leverage) and three counterfactual exercises (high noise-low leverage, high noise-high leverage, low noise-high leverage).

Comparing the baseline (column 1) and the first counterfactual model (column 2), we see that, ceteris paribus, having noisier signals leads to higher 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

[17] We illustrate this point in Figure A.1 in the appendix. In the crisis, signals become pessimistic, which put downward pressure on the price of debt q (panel a). Simultaneously, the firm's fundamental z deteriorates, and in equilibrium leverage decreases (panel b). The additional impact of noise is larger on the price than the quantity of debt, as it has a direct effect on the former: lenders demand an even larger premium due to the Jensen's effect (panel a), whereas the noise does not any directly affect the firm's demand for credit (since the firm can observe z) besides through its effect on price (panel b).

[18] Note that the spreads without noisy signals are still higher than the spreads implied by a model with full information, as shown in Figure 5. This is because even without noisy signals, there is still asymmetric information in the model; in other words, investors are still uncertain about the firm's default probability in each period.

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 7, 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.

5.5 Extensions to Alternative Learning Rules

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

First, in the models with optimism/pessimism, we calibrate the model to target the historical average default rates for firms issuing high-yield bonds and investment-grade bonds, respectively. We show that the model with pessimistic investors produces higher and more volatile spreads than the model with optimistic investors, which are patterns consistent with the data on high-yield corporate bonds and investment-grade bonds, respectively. In addition, the model generates a comparable (and untargeted) spread between the high-yield and investment-grade. Next, in the model with near-rational learning, the levels of spread and investment are similar to those in the baseline model, but aggregate volatility is unambiguously higher, especially if investors make mistakes more often. Finally, we show that augmenting the rational learning model with overextrapolation improves the model fit on some aggregate moments, such as the business cycle correlations, and it further increases the level and volatility of spreads.

Overall, these model extensions show that while learning from public signals represents one potentially important force at play, there are likely other mechanisms that matter. As such, learning does not negate but rather complements existing behavioral explanations.

6 Supporting Evidence

The mechanism at the core of our theory is testable and predicts that fluctuations in expectations of corporate profits should drive credit spreads and corporate investment. In turn, another important testable implication is that fluctuations in expectations are a source of macro fragility, as they make credit spreads and investment more volatile over the cycle. In this section, we turn to micro data to offer more direct evidence in support of the mechanism.

To that end, we construct a quarterly measure of forecast revisions at the firm level, Rev_{it}. Using the same approach as equation (2), the firm-level measure is defined as the change between current and last period's forecasts of next quarter corporate profits. We retrieve data on analyst-by-analyst EPS forecasts for one quarter ahead from the I/B/E/S Detail History File (unadjusted).[19] Using the detailed analyst-by-analyst forecasts, we calculate the firm-level consensus EPS forecast as the median of all analysts' forecasts for the relevant period. We avoid using the off-the-shelf consensus forecast from the I/B/E/S Summary History File because it is known to be problematic due to backfilling and stale information among other issues (see, for example, Bouchaud, Kruger, Landier, and Thesmar, 2019). We then merge the firm-level measure of forecast revisions with monthly bond-level spreads from ICE/IDC for 1998-2010, which has comparable coverage to the formerly available Merrill Lynch database, and from the Warga database (via Mergent FISD) for 1982-1997. Quarterly firm balance sheet information is from Compus-

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

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

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

The negative (positive) relation between changes in expectations of corporate profits and corporate credit spreads (investment) is robust to two additional tests, which refine identification by isolating plausibly exogenous variation in revisions or "shocks" to expectations. An important concern with both our time-series and baseline cross-sectional estimates is that they may erroneously pick up omitted macro variables, such as those related to other theories of the business cycle. For example, a contraction in bank lending may lead to higher spreads and, in turn, harm future profitability. Revisions are clearly an endogenous outcome that may be driven by these shocks, rather than an independent driving force of the cycle. To address this issue, which is an instance of a standard endogeneity problem, we use two empirical strategies: first, similar to Fracassi, Petry, and Tate (2016), we construct a measure of "shocks" to revisions based on analyst–specific change in expectations. The analyst–specific shocks are estimated using a regression-based decomposition method as the analyst-quarter effects in an analyst-level regression of quarterly revisions that also includes firm-quarter effects to control for (changes in) firm fundamentals. This approach compares each analyst's revisions only with those of peers who make forecasts for the same firm in the same quarter, thus deriving estimates of analyst effects that are orthogonal to firm fundamentals. We calculate the average of the resulting analyst-specific shocks within a given firm-quarter to construct the firm-level shock.

Second, we use a quasi-natural experiment that exploits plausibly exogenous variation in revisions around 15 brokerage house mergers between 1982 and 2005 that affect over 500 firms for which we have complete information on revisions. The source of identification here is that, as documented by Hong and Kacperczyk (2010), these mergers reduce competition and lead to an increase in optimism bias for firms covered by both merging houses before the merger – i.e., they have a positive effect on revisions, which is plausibly unrelated to firm fundamentals. To ensure that we are not capturing just changes in analyst coverage, we exclude observations involving brokerage house closures, as these events have been shown to affect the information environment and the firm incentives to produce public information (see, for example, Balakrishnan, Billings, Kelly, and Ljungqvist, 2014).

The results for these two approaches are shown in Columns (5)-(10) of Table 8. The estimates for spreads and investment remain large and strongly statistically significant under either approach. This evidence helps to distinguish our mechanism from other macro theories because it shows that changes in expectations matter for spreads and investment even after we control for aggregate shocks by including time effects and for changes in firm fundamentals via our two identification strategies. The evidence also helps to distinguish our mechanism from behavioral theories of the credit cycle that emphasize diagnostic expectations (e.g., Bordalo, Gennaioli, and Shleifer, 2018, Bordalo, Gennaioli, Shleifer, and Terry, 2019). In these theories, though changes in expectations amplify the cycle, the ultimate driving forces of the cycle remain changes in fundamentals. As such, the evidence that even after controlling for changes in fundamentals there is an independent role for expectations, indicates that learning and diagnostic expectations are distinct and complementary mechanisms.

Finally, we use an aggregate counterfactual and sample-split analysis to examine whether the data supports the main implication of the model that fluctuations in expectations are a source of macro fragility. The regression-based counterfactual exercise compares the actual annual contraction in aggregate investment in the great recession (i.e., between 2007Q4 and 2009Q2 as per the NBER cycle dates) to that implied by an in-sample prediction based on the regression estimate in Column 3 of Table 8. Specifically, the counterfactual annual contraction in aggregate investment is calculated by "shutting off" the effect of negative revisions (i.e., by adding back to the predicted growth the part due to negative revisions, which is based on the regression estimate of $0.332 \times Rev_{it}$, for observations with below median revisions). The difference between the actual contraction in aggregate investment and the counterfactual is about 5 percentage points, which is roughly a quarter of the overall contraction, indicating that our mechanism fluctuations in expectations were an economically important source of macro fragility in the Great Recession.

Table 9 uses sample-split analysis to offer additional cross-sectional evidence. We regress changes in spreads and investment on a "Crisis" indicator that is equal to one between 2007Q4 and 2009Q2. The resulting estimate measures the average size of the change in spreads and investment in the crisis and sub-sequent Great Recession. We split the sample based on proxies for the type of information frictions that are emphasized by our model. First, we consider whether firms had negative earnings revisions, which we proxy by splitting the sample based on whether firms are above or below the median of Revit. In line with the unique prediction of our model, firms with the most negative revisions experienced an about 50% bigger spike in spreads and twice as large a contraction in investment (Columns (1)-(2)).

Second, we further stratify the sample based on whether firms with the most negative revisions also had their debt rated as junk (triple B or lower, Column (3)). Third and final, we consider a sub-sample of firms where analysts are most reliant on public signal (Column (4)). Based on our model, these firms should be most sensitive to macro conditions. To measure reliance on public signal, we follow Chen and Jiang (2006) and use analyst-level regressions to calculate for each analyst the correlation between forecast errors[20] and deviations from consensus forecast (see their equation 7). Because a negative (positive) correlation is indicative of over-weighting of the public (private) signal, we classify as *Most Reliant on Public Signal* those firms whose analysts have a correlation below the mean. Consistent with the cost of debt financing for junk-rated firms being the most information sensitive, the spike in spreads was outsized for these firms. As it was for firms whose analysts were most reliant on the public signal, which also experienced a large contraction in investment. Overall, the firm-level data supports the central tenet of our theory that changes in expectations are an important driver of credit spreads and investment over the cycle.

7 Extended Model in General Equilibrium

In this section, we extend our model to a general equilibrium setting to better understand the aggregate impact of information frictions in the credit market on consumption

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

and employment. The main difference from our baseline model is the introduction of households, which have preferences over consumption and labor.

7.1 Setup

There are continuums of firms, financial intermediaries, and households. The firms are competitive, and they use capital and labor to produce, subject to productivity of operation shocks. They can borrow state-uncontingent debt from financial intermediaries to finance a portion of their input costs, and they are allowed to default. Households own all the firms, and choose consumption and labor in each period. Financial intermediaries are competitive, and they extend credit to firms.

Households Households choose their consumption C and hours worked l by solving the following problem:

$$\begin{aligned} V^H(k,b,a,\tilde{z},z) = & \max_{C,h}\ u(C,h) \\ & + \beta \int_{\underline{a}}^{\overline{a}} \int_{\underline{z}}^{\overline{z}} \int_{\underline{z}}^{\overline{z}} V^H(k',b',a',\tilde{z}',z') P(z,dz') P(\tilde{z},d\tilde{z}') Q(a,da') \\ \text{s.t.} \quad & C \leq wh + s + e + T. \end{aligned} \tag{19}$$

The per-period utility function $u(C,h)$ is assumed to be strictly increasing and concave in consumption C, and strictly decreasing and concave in hours worked h. To maintain tractability, we assume a simple functional form, $u(C,h) = \frac{C^{1-\gamma}}{1-\gamma} - \theta h$.

In the budget constraint, w is real wage, e denotes the dividends from firms, T is a rebate of the corporate income tax revenues to the household. The household's intertemporal decisions are determined by the stochastic discount factor (SDF), $M_{t,t+1} = \beta \frac{u'(C')}{u'(C)}$.

Firms Firms' problem is the same as in Section 3 with two exceptions. First, now firms use both labor and capital in production, with the following technology:

$$y = a^{(1-\chi)\alpha} \left(k^{\chi} h^{1-\chi}\right)^{\alpha}$$

where $\chi \in (0,1)$ is the value-added share of capital, and $\alpha < 1$ governs the degree of decreasing returns in production as before. a is aggregate productivity, and $(1-\chi)\alpha$ is a normalization factor to ensure that the firm's profit function is linear in a (see Gilchrist, Sim, and Zakrajšek, 2014). Hence firms' intratemporal labor demand satisfies:

$$\pi(a,w,k) = \max_{h \geq 0} \left\{ a^{(1-\chi)\alpha} \left(k^{\chi} h^{1-\chi}\right)^{\alpha} - wh \right\} = a\psi(w)k^{\eta}$$

where

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

and we can write firm's before-tax profit as $a\psi(w)k^{\eta} - z$, and substitute this in the firm's equity value $J(k,b,z,a,\tilde{z})$. The second difference from our baseline model is that now firms' future equity values in (11) are discounted by the household's SDF, since household is the owner of firms.

Financial intermediaries We continue to assume that there is information friction in the bond market. Specifically, we assume that firms and households (owners of firms) can observe z, but financial intermediaries, which are perfectly competitive, cannot. Instead, they must form their estimate of it according to (8). As they observe b' and k', they use their estimate $\tilde{z}$ to determine the price of bond $q(b',k',\tilde{z},a)$, which still satisfies the no-arbitrage condition (13).

Market clearing To close the model, the labor and goods market clearing conditions are given by:

$$\begin{aligned} &h^s = h^d \\ &C + i = y - g(k',k) - \Lambda(e) - z + \tilde{R}^b, \end{aligned}$$

respectively. In the aggregate resource constraint, recall that $g(k',k)$ is the investment adjustment cost (5), $\Lambda(e)$ is the equity issuance cost (6), and z is the cost of operation (4). $\tilde{R}^b$ denotes the ex-post profits or losses made by the financial intermediaries after debt settlement. The bond market clears by the Walras' law.

7.2 Quantitative Analysis

There are three additional parameters in the extended model, which are χ, γ, and θ.[21] We set the capital share to be $\chi = 0.36$, which is a common value in the literature. For tractability, we set $\gamma = 1$, so the household's per-period utility is given by $u(C,h) = \log C - \theta h$. The weight of the disutility of hours worked θ is chosen so that the real wage in the steady state is equal to one. To maintain comparability with our baseline model, we target the same moments as before. All the moments and their data counterparts are reported in Table 10. Again we compare the business cycle moments of the two economies, with the only difference being whether financial intermediaries can observe

[21] Table A.4 summarizes the parameter values in the extended model.

the firms' cost of operation z.

There are three main observations from Table 10. First, the benchmark economy exhibits the hallmark features of an RBC model, with the investment about three times more volatile than output and highly correlated with output, consumption, and hours worked. Second, one of our main findings from the baseline model is robust in the GE extension: spreads and defaults are both counter-cyclical. Third, comparing the two economies in Table 10, the full information model exhibits lower volatilities for consumption, employment and investment. This is because the asymmetric information problem in the bond market affects the aggregate variables through firm's hiring/investment decisions as well as households' budget constraint.

8 Conclusion

In order to better understand the consequences of information imperfections and learning in debt markets, we have combined macro and micro data on professional forecasts of corporate profits, bond returns, and corporate investment with a novel model of credit cycles. Consistent with the idea that debt investors form beliefs about firms' creditworthiness using publicly-available information on short-term corporate profits, we have documented that changes in quarter-ahead professional forecasts of corporate profits have strong predictive power for credit spreads and investment over long horizons, both in the aggregate and at the firm level. Second, and perhaps more important as a contribution, we have developed a quantitative model that incorporates this mechanism and shown that its ability to account for key stylized facts of the credit cycles is superior to the rational learning benchmark. As such, our model provides a plausible basis for informational inefficiencies in credit markets to be a source of fragility for 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, it would be interesting to add agency issues in equity markets and explore whether they reinforce our mechanism. Second, an advantage of our quantitative model is that it can be readily extended for policy evaluation of alternative financial stability tools. Such an extension would allow for quantitative and welfare evaluation of policy counterfactuals of the effectiveness of monetary policy or other policy measures aimed at stabilizing financial markets in times of stress. Finally, our framework could be extended to study in more detail additional forces that may lead to fragility in credit markets, including, for example, relative-performance evaluation type features in institutional investors' compensation contracts (Feroli, Kashyap, Schoenholtz, and Shin, 2014) 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 learning is a central idea in modern financial economics.

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

Panels A and B of this table present summary statistics for our aggregate variables, the two main explanatory variables over our sample period from 1971-2010 (Panel A) and the main outcomes (Panel B). We measure investor expectations of corporate profits, Rev_t, as the current revision in investors' expectations of next quarter corporate profits. The measure is contructed as the change between current and last period's investor expectations of next quarter corporate profits. We measure noise in investor expectations of corporate profits, σ_t, as the dispersion (standard deviation) of revisions across individual forecasters. To ease economic interpretation, the measures are re-scaled by their respective unconditional standard deviation. Quarterly information on expectations at the aggregate level is from the Survey of Professional Forecasters.

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

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

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

Panels C and D of this table present summary statistics for our firm-level variables, the main explanatory variables over our sample period from 1982-2010 (Panel C) and the main outcomes (Panel D). We measure investor expectations of corporate profits, Rev_{it}, as the current revision in investors' expectations of next quarter corporate profits. The measure is contructed as the change between current and last period's investor expectations of next quarter corporate profits. To ease economic interpretation, the measures are re-scaled by their respective unconditional standard deviation. Quarterly information on expectations at the firm level is from IBES. We also consider a residualized version of Rev_{it}, *Shock to* Rev_{it}, which is constructed as the analyst-specific component which is orthogonal to the firm-specific component of Rev_t. *Reliance on Public Signal*$_{it}$ is based on Chen and Jiang (2006) and is defined as the correlation between forecast errors and deviations from consensus forecast, with a negative correlation indicating over-weighting of the public signal. Bond-level spreads are monthly from ICE/IDC for 1998-2010 and from the Warga database for 1982-1997. Quarterly firm balance sheet information is from Compustat.

Panel C: Expectations of Corporate Profits, Firm Level (1982-2010)				
	Mean	St.Dev	Min	Max
Rev_{it}	-0.64	1.00	-5.36	1.67
Shock to Rev_{it}	0.01	1.00	-3.45	3.28
Reliance on Public Signal$_{it}$	-0.32	1.00	-3.69	2.48
Obs=245,908				
Firms=10,396				

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

Table 2: Multivariate Forecasting Regressions of Credit Spreads

This table summarizes results of multivariate time-series forecasting regressions of excess bond returns on investor expectations of corporate profits, controlling for macroeconomic conditions (aggregate consumption, business investment, GDP, and corporate profitability (ROA)), excess stock returns, short and long rates (1–year Treasuries and the effective Fed Fund Rate), the term spread, and lagged excess returns:

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

X_t is our measure of expectations of corporate profits and its noise, in turn, in each quarter. We measure investor expectations of corporate profits, Rev_t, as the current revision in investors' expectations of next quarter corporate profits. The measure is constructed as the change between current and last period's investor expectations of next quarter corporate profits. We measure noise in investor expectations of corporate profits, σ_t, as the dispersion (standard deviation) of revisions across individual forecasters. To ease economic interpretation, the measures are re-scaled by their respective unconditional standard deviation. Quarterly information on expectations is from the Survey of Professional Forecasters. In Panel A, the dependent variable is the 1-, 2-, 3-, 4- or 8-quarter cumulative excess return on corporate bonds. In Panels B-C, we show robustness to alternative mechanism. The dependent variable is the 4- or 8-quarter cumulative excess return on corporate bonds, the explanatory variable is Rev_t, and we add controls for alternative explanations (Panel B) or orthogonalize Rev_t with respect to the alternatives (Panel C). t-statistics for k-period forecasting regressions are based on Newey-West (1987) standard errors allowing for serial correlation up to k-1 lags, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: Excess Return on Corporate Bonds

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

Panel B: Robustness to Controlling for Other Mechanisms

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

Panel C: Robustness to Orthogonalizing Rev_t by

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

Table 3: 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:

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

$\widehat{R}_{t\rightarrow t+k}$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 contructed as the change between current and last period's investor expectations of next quarter corporate profits. We measure noise in investor expectations of corporate profits, σ_t, as the dispersion (standard deviation) of revisions across individual forecasters. To ease economic interpretation, the measures are re-scaled by their respective unconditional standard deviation. Quarterly information on expectations is from the Survey of Professional Forecasters. In Panel A, $\widehat{R}_{t\rightarrow t+k}$is the predicted 4- or 8-quarter cumulative excess return on corporate bonds. In Panels B and C, we examine robustness to using two alternative measures of excess returns, the predicted 4- or 8-quarter cumulative excess return on BBB-minus rated corporate bonds relative to AAA-rated bonds (Panel B) and the predicted 4- or 8-quarter cumulative excess bond premium by Gilchrist and Zakrajšek (2012). Robust t-statistics are shown in brackets, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

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

Table 4: 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.3)	Persistence of signal	Revision in expected profit
σ_u (see Table A.3)	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 5.

Table 5: Model Fit

Panel A: Targeted moments	**Data**	**Model**	**Full information model**
	(1)	(2)	(3)
Investment rate (mean)	0.018	0.024	0.027
Leverage (mean)	0.267	0.309	0.318
Profit to asset (mean)	0.053	0.067	0.071
Default rate	0.013	0.010	0.011
Panel B: Untargeted moments	**Data**	**Model**	**Full information model**
	(1)	(2)	(3)
Bond spread (mean)	0.019	0.017	0.009
σ(spread)	2.10	2.58	1.97
Corr(spread, output)	-0.57	-0.31	0.47
σ(default)	0.012	0.007	0.006
Corr(default, output)	-0.43	-0.17	0.35
σ(invest)/σ(output)	3.46	2.75	2.36
Corr(invest, output)	0.57	0.74	0.68
Panel C: Economic Significance			
Average spread, crisis		4.36	
Counterfactual average spread, crisis		2.48	
Annualized change in investment, crisis		-11.2	
Counterfactual change in investment, crisis		-8.6	

Note: Panel A reports the targeted moments. Panel B reports the untargeted fit of the model. Column (1) presents the data moments calculated from the Compustat between 1985Q1 and 2010Q4. Columns (2) and (3) compare 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 so the price of debt is a function of z_t (see equation (A.1)). In Panel C, we report the average spread and annualized change in investment, respectively, during the 2007-09 crisis in two economies: the baseline model, and a counterfactual model in which we replace the actual revisions during crisis with the pre-crisis average.

Table 6: Model-Implied Forecasting Regressions

Panel A: Expected Corporate Profits and Credit Spreads

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

	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

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

	Inv 4-qtr	Inv 8-qtr		Output 4-qtr	Output 8-qtr
β	-0.836	-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 $R_{t\to t+k}$ 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 $BC_{t\to t+k}$ is the 4-, or 8-quarter ahead investment and output, respectively. The independent variable $\hat{R}_{t\to t+k}$ is the predicted 4- or 8-quarter cumulative excess return on corporate bonds, estimated from the forecasting regression in Panel A.

Table 7: 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 4. 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 8: Expectations of Corporate Profits, Credit Spreads, and Investment – Supporting Cross-sectional Evidence

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

$$R_{it\to it+k} = \alpha + \beta X_{it} + \gamma Controls_{it} + u_{it+k}$$

X_{it} is our measure of expectations of corporate profits for each firm, i, in each quarter, t. We measure investor expectations of corporate profits, Rev_{it}, as the current revision in investors' expectations of next quarter corporate profits (Columns 1-4). The measure is contructed as the change between current and last period's investor expectations of next quarter corporate profits. To ease economic interpretation, the measures are re-scaled by their respective unconditional standard deviation. Quarterly information on firm-level expectations is from IBES. In Panel A, the dependent variable is the 4- or 8-quarter cumulative excess return on corporate bonds. In Panel B, the dependent variable is the 4- or 8-quarter-ahead change in capital expenditures. The firm-level controls are size and current profitability (ROA). To refine identification, Columns 5-8 report results for a residualized version of Rev_{it}, *Shock to* Rev_{it}, which is constructed as the analyst-specific component which is orthogonal to the firm-specific component of Rev_{it}; and Columns 9-10 report results for a 2SLS-IV estimation that uses brokerage house mergers from Hong and Kacperczyk (2010) to instrument for Rev_{it}. t-statistics are based on standard errors that are clustered at the firm level to allow for within-firm serial correlation with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: Excess Return on Corporate Bonds										
	Rev_{it}				Shock to Rev_{it}				Instrumented Rev_{it}	
	Full Sample		Crisis (2005-2010)		Full Sample		Crisis (2005-2010)		Full Sample	
	4-qtr	8-qtr	4-qtr	8-qtr	4-qtr	8-qtr	4-qtr	8-qtr	4-qtr	8-qtr
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
β	-0.212	-0.182	-0.284	-0.194	-0.030	-0.096	-0.150	-0.114	-0.244	-0.393
[t]	[-5.34]	[-3.28]	[-5.78]	[-3.88]	[-2.41]	[-3.93]	[-5.45]	[-3.89]	[-2.20]	[-3.18]
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	149,403	119,548	46,741	37,117	141,533	126,663	44,931	35,423	27,664	24,080
Bonds	4,118	3,513	1,660	1,349	4,027	3,728	1,630	1,322	1,001	950
R^2	0.18	0.13	0.15	0.12	0.13	0.13	0.14	0.12		
Panel B: Investment										
	Rev_{it}				Shock to Rev_{it}				Instrumented Rev_{it}	
	Full Sample		Crisis (2005-2010)		Full Sample		Crisis (2005-2010)		Full Sample	
	4-qtr	8-qtr	4-qtr	8-qtr	4-qtr	8-qtr	4-qtr	8-qtr	4-qtr	8-qtr
β	0.282	0.256	0.332	0.258	0.136	0.109	0.210	0.346	0.348	0.364
[t]	[25.88]	[24.62]	[9.74]	[7.93]	[7.91]	[6.05]	[6.95]	[7.78]	[3.31]	[3.70]
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	176,714	157,346	29,040	18,333	122,395	111,595	25,217	16,176	30,629	29,016
Firms	8,576	7,805	3,470	3,052	6,587	6,128	3,006	2,707	524	519
R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01		
Economic Significance: Aggregate Counterfactual										
Aggregate Annual Change in Inv, Crisis				-19.83						
Counterfactual Agg. Ann. Change in Inv, Crisis				-15.01						

Table 9: Expectations Driven Credit Cycles – Additional Supporting Evidence

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

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

$Crisis_t$ is an indicator that takes value of one between 2007Q4 and 2009Q2, the sample period is 2005-2010 and the firm-level controls are size and current profitability (ROA). We measure investor expectations of corporate profits, Rev_{it}, as the current revision in investors' expectations of next quarter corporate profits. The measure is contructed as the change between current and last period's investor expectations of next quarter corporate profits. Quarterly information on expectations at the firm level is from IBES. In Panel A, the dependent variable is the quarterly change in corporate bond spreads and we split the sample based on the mean of Rev_{it} (Columns 1-2) and on junk-rated bond status (Column 3). For the latter, we also consider a measure of reliance on public signal based on Chen and Jiang (2006), which is defined as the correlation between forecast errors and deviations from consensus forecast. Because a negative correlation is indicative of over-weighting of the public signal, we classify as *Most Reliant on Public Signal*$_{it}$ those firms that are below the mean of the measure (Column 4). In Panel B, the dependent variable is the quarterly change in capital expenditures and we split the sample based on the mean of Rev_{it} (Columns 1-2) and on junk-rated firm status (Columns 3) as well as on *Most Reliant on Public Signal*$_{it}$ (Column 4). t-statistics are based on standard errors that are clustered at the firm level to allow for within-firm serial correlation with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: Corporate Bond Spreads' Spike in the Crisis				
	Most Negative Rev_{it}		Junk Rated &	
	Yes	No	Most Negative Rev_{it}	Most Reliant on Public Signal$_{it}$
	[1]	[2]	[3]	[4]
β	0.607	0.414	1.230	1.257
[t]	[18.08]	[15.21]	[8.98]	[9.22]
Bond FE	Yes	Yes	Yes	Yes
Obs	23,560	32,019	3,637	3,913
Bonds	1,491	1,746	333	304
R^2	0.15	0.10	0.24	0.18
Panel B: Investment Contraction in the Crisis				
	Most Negative Rev_{it}		Most Negative Rev_{it}&	
	Yes	No	Junk Rated	Most Reliant on Public Signal$_{it}$
β	-0.618	-0.296	-0.661	-0.662
[t]	[-10.69]	[-6.31]	[-5.62]	[-8.71]
Firm FE	Yes	Yes	Yes	Yes
Obs	19,476	22,620	5,027	6,235
Firms	2,900	3,288	726	1,194
R^2	0.12	0.12	0.10	0.15

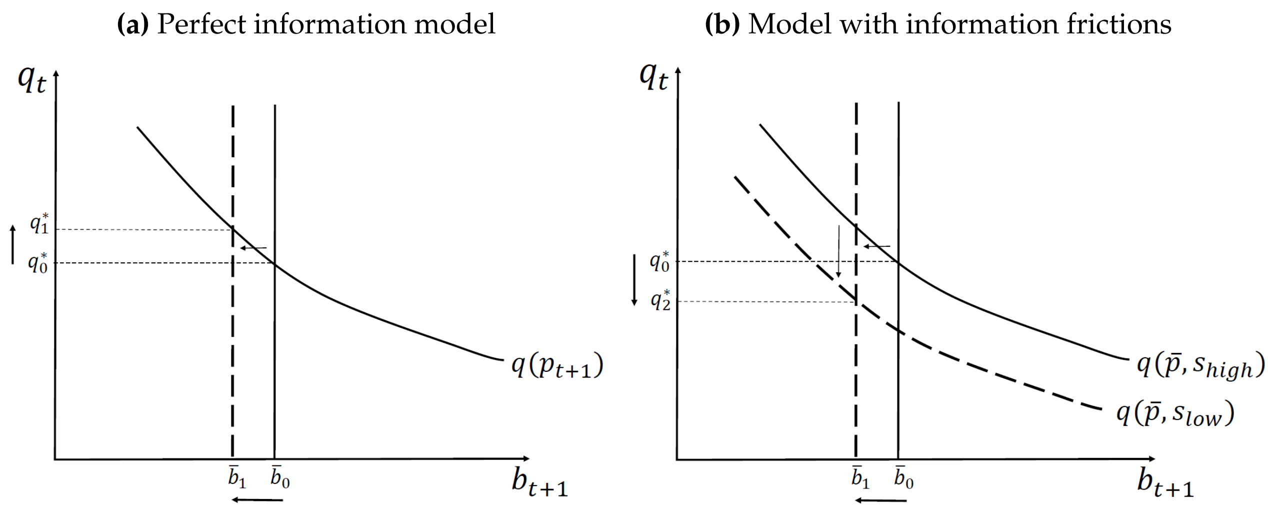
Table 10: Model Fit: GE Extension

Panel A: Targeted moments	**Data**	**Model**	**Full information model**
	(1)	(2)	(3)
Investment rate (mean)	0.018	0.022	0.025
Leverage (mean)	0.267	0.291	0.298
Profit to asset (mean)	0.053	0.047	0.050
Default rate (mean)	0.013	0.007	0.009

Panel B: Untargeted moments	**Data**	**Model**	**Full information model**
	(1)	(2)	(3)
Spread			
Bond spread (mean)	0.019	0.015	0.010
σ(spread)	2.10	2.51	1.92
Corr(spread, output)	-0.57	-0.29	0.31
Default risk			
σ(default)	0.012	0.005	0.005
Corr(default, output)	-0.43	-0.19	0.28
Investment			
σ(invest)/σ(output)	3.46	2.60	2.28
Corr(investment, output)	0.57	0.61	0.65
Consumption			
σ(consume)/σ(output)	0.42	0.89	0.82
Corr(consumption, output)	0.56	0.93	0.95
Employment			
σ(employ)/σ(output)	0.60	0.24	0.18
Corr(employment, output)	0.65	0.43	0.46

Note: Panel A reports the targeted moments in the GE model; panel B reports the untargeted fit of the model. Column (1) presents the data moments calculated from the Compustat between 1985Q1 and 2010Q4. Columns (2) and (3) compare 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 is a function of the public signal (s_t). In the model without information frictions, investors can observe the firm's state z_t so the price of debt is a function of z_t.

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:

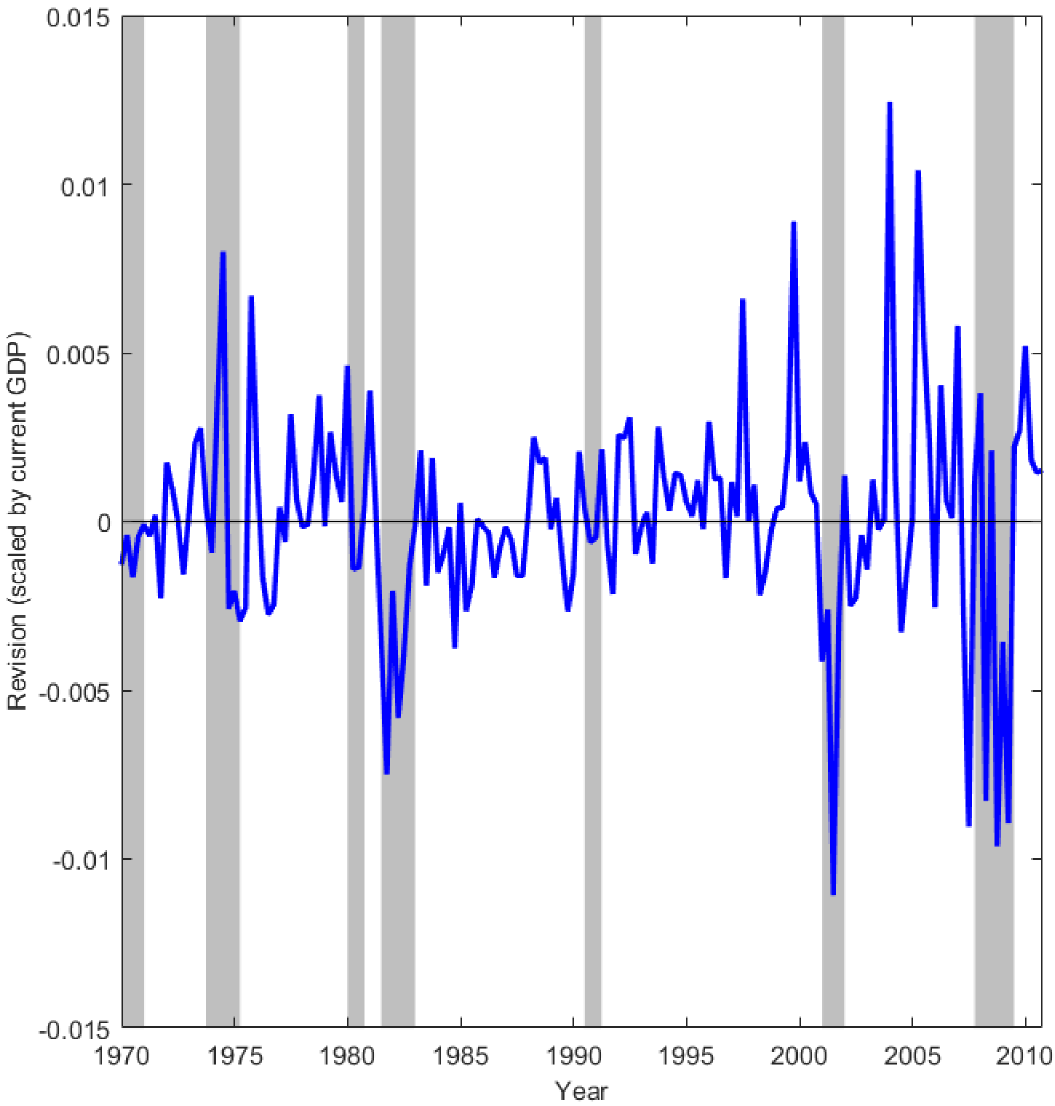
$$q_t = \beta\Big(\tilde{B} + (1-\tilde{B})p_{t+1}\Big).$$

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:

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

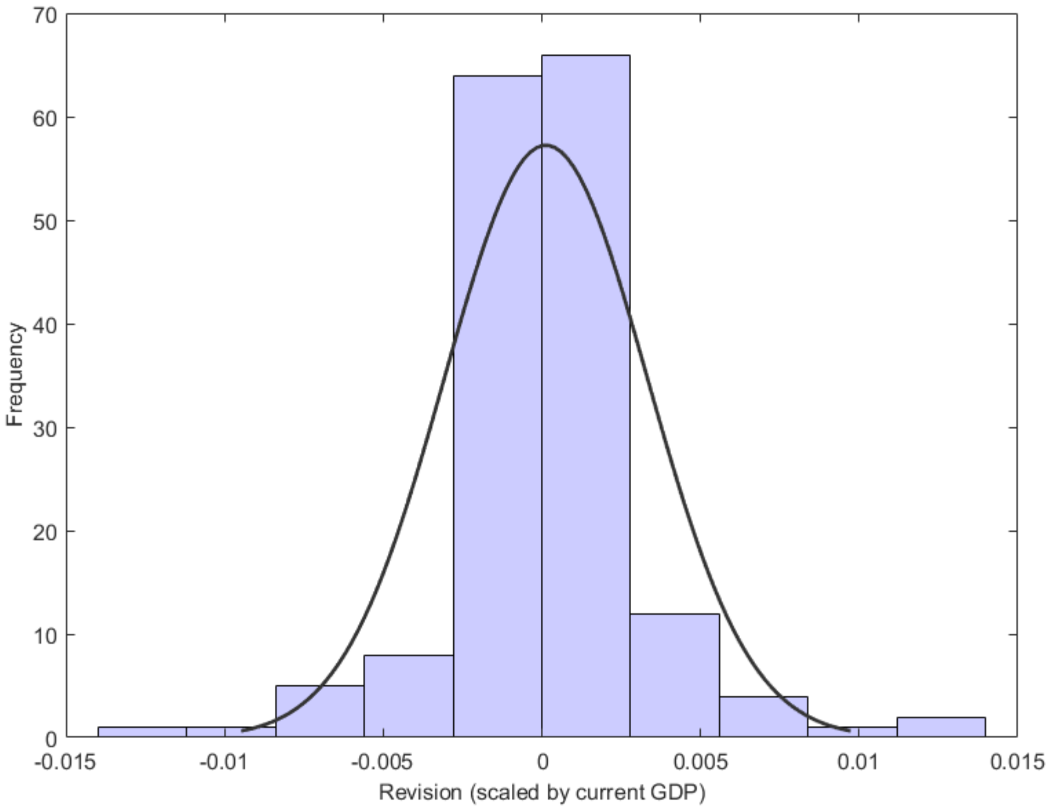
Therefore, in addition to the reduction of firm borrowing from $\bar{b}_0$ to $\bar{b}_1$, investors receive a more pessimistic signal about the firm's credit worthiness in a recession, so the demand curve shifts down from $q(\bar{p}, s_{\text{high}})$ to $q(\bar{p}, s_{\text{low}})$.

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



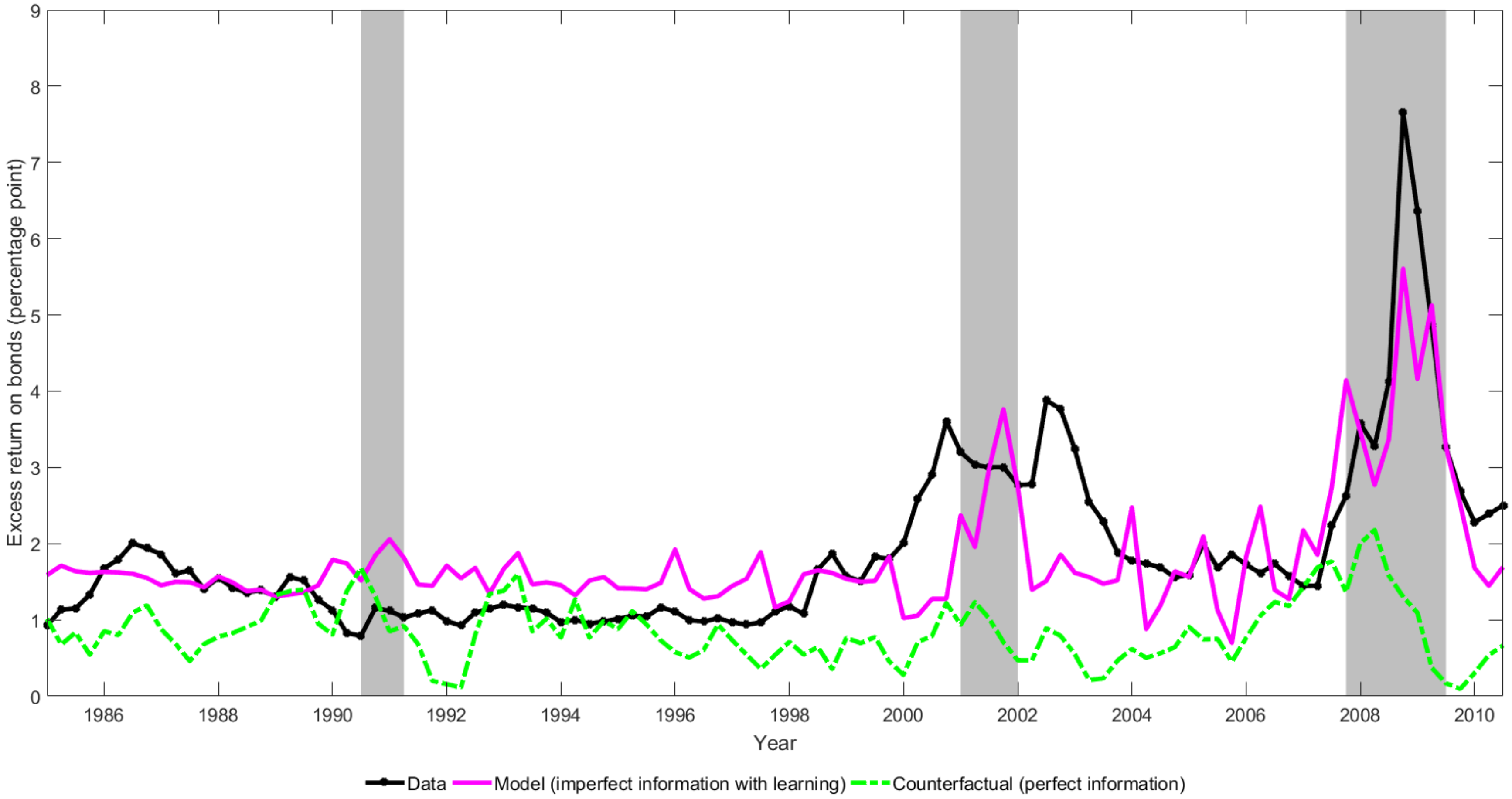
Note: This figure shows the current revision in investors' expectations of next quarter's corporate profit between 1970Q1 and 2010Q4, divided by the US GDP. Data is from the Survey of Professional Forecasters. Shaded areas indicate the NBER recession dates.

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
Online Appendix

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December 2019

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 (4) 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 (3) and (4) 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.[22] 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 $V_1(k',b',z',a',\tilde{z}') = V_0^{*}(k,b,z,a,\tilde{z})$;
   - 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 $q_1(b',k',\tilde{z},a)$;

[22]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.3). 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.

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

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

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 $\tilde{z}$:

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

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

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

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 Alternative Learning Rules

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

Optimism and Pessimism

In our context, 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:

$$\tilde{z}^{\text{bias}} = \tilde{z} + \psi, \tag{A.5}$$

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.[23] 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.5 and A.6 summarize the parameter values in each set of calibration. Columns (3) and (4) of Table A.7 report the

[23] 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.5 and A.6).

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.

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:

$$\tilde{z}^{\mathrm{NR}} = (1-\omega)\tilde{z} + \omega\eta, \tag{A.6}$$

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 (A.6) is a weighted average of the updating process under rational learning and a random error.

We solve the model under the new updating rule (A.6), under the same parameterization as the baseline model with rational learning (Table 4). 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 A.7.

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.

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 4). We use empirical estimates of overextrapolation from Landier, Ma, and Thesmar (2019) to calibrate ζ.[24]

Quantitatively, the last two columns of Table A.7 illustrate that augmenting the rational learning model with overextrapolation improves the model fit on some aggregate moments, such as the business cycle correlations. For instance, the baseline model can account for approximately 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.

[24]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.

E Additional Tables and Figures

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

This table summarizes additional robustness results of multivariate time-series forecasting regressions of excess bond returns on investor expectations of corporate profits, controlling for macroeconomic conditions (aggregate consumption, business investment, GDP, and corporate profitability (ROA)), excess stock returns, short and long rates (1–year Treasuries and the effective Fed Fund Rate), the term spread, and lagged excess returns:

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

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

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

Table A.2: Additional Business Cycle Outcomes

This table summarizes additional robustness results of multivariate time-series forecasting regressions of business cycle aggregates on the component of excess bond returns that is predictable based on investor expectations of corporate profits, controlling for macroeconomic conditions (aggregate consumption, business investment, GDP, and corporate profitability (ROA)), excess stock returns, short and long rates (1–year Treasuries and the effective Fed Fund Rate), the term spread:

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

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

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

Table A.3: 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.4: Parameterization in GE Model

Parameter	**Description**	**Target**
Preferences and technology		
$\chi = 0.36$	Capital share	Gomes et al. (2016)
$\alpha = 0.65$	Returns to scale	Hennessy and Whited (2007)
$\delta = 0.025$	Depreciation rate	NIPA depreciation
$\beta = 0.99$	Time preference	Annual risk-free rate 4%
$\gamma = 1$	Risk aversion	log utility in consumption
$c_k = 0.670$	Adjustment cost	Mean investment rate
$\mu_z = 19.21$	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)
$\xi = 0.22$	Bankrupty cost	Mean default rate
$c = 0.0101$	Coupon rate	Price of default-free debt
$\lambda = 0.05$	Debt amortization rate	Average debt maturity
$c_e = 0.160$	Equity issuance cost	Mean leverage ratio
$B^{\max} = 0.69$	Maximum recovery rate	Top decile recovery rate
Learning		
ρ_s (see Table A.3)	Persistence of signal	Revision in expected profit
σ_u (see Table A.3)	Volatility of noise in signal	Revision in expected profit

Note: This table presents the calibrated parameters in the general equilibrium model with rational learning (section 7. The targeted moments and their data counterparts are reported in Table 10.

Table A.5: 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.3)	Persistence of signal	Revision in expected profit
σ_u (see Table A.3)	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.6: 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.3)	Persistence of signal	Revision in expected profit
σ_u (see Table A.3)	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.

Table A.7: 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.5 and A.6). The parameter values in the near rational and overextrapolation models are those reported in Table 4.

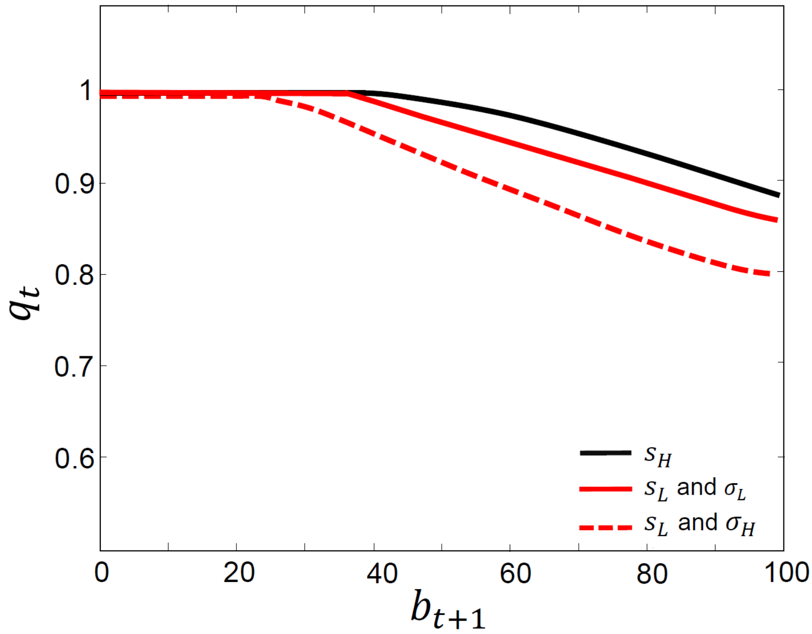
Table A.8: Robustness Check:
Model without Equity Financing

	Data (1)	**Baseline** (2)	**Without equity** (3)
First moments			
Default rate	0.013	0.010	0.012
Bond spread	0.019	0.017	0.022
Leverage	0.267	0.309	0.289
Investment	0.018	0.024	0.026
Second moments			
Corr(default, output)	-0.43	-0.17	-0.26
Corr(spread, output)	-0.57	-0.31	-0.39
Corr(invest, output)	0.57	0.74	0.78
σ(spread)	2.10	2.58	2.67
σ(default)	0.012	0.007	0.011
σ(invest)/σ(output)	3.46	2.75	2.82

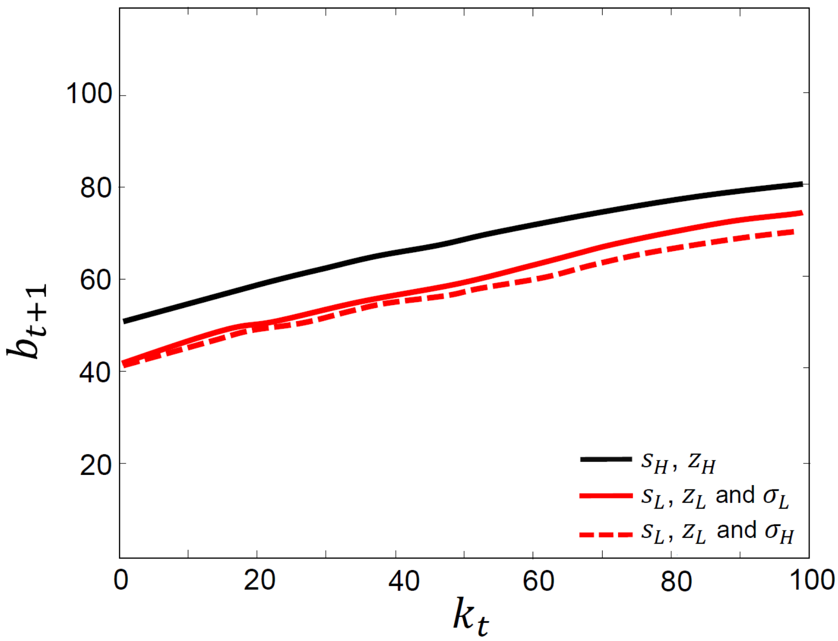
Note: This table compares the model-generated moments in the model with and without equity financing. In the counterfactual model, firms face a non-negative dividend constraint in each period, i.e. $e_t \geq 0$, so debt is their only source of external financing. The targeted moments are the same as in the baseline model: investment rate, leverage, profit to asset, and default rate. In the baseline model, we calibrate the equity issuance cost c_e to target the mean leverage, whereas in the counterfactual model, we use the maximum recovery rate of bonds, $B^{\max}$, to target leverage.

Figure A.1: Policy Functions

(a) Debt price $q(b', k', \tilde{z}(s), a)$

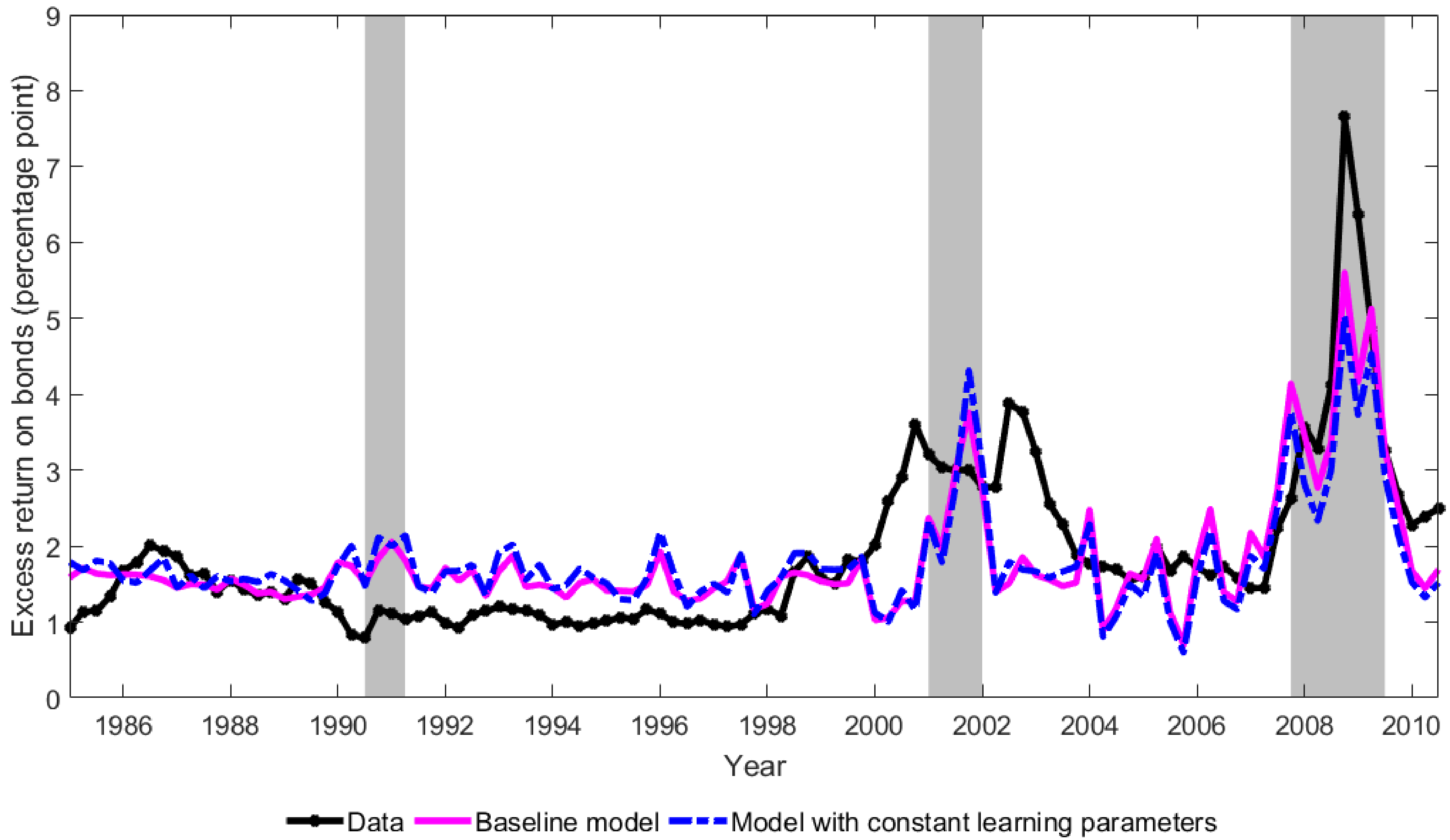


(b) Debt $b'(b, k, \tilde{z}(s), a, z)$



Note: This table shows the policy functions in the baseline model (section 3) with rational learning, for different levels of aggregate shocks. Panel (a) plots the price of debt as a function of b', given k', a, and two different levels of the signal, s_{low} and s_{high}. Panel (b) plots the optimal level of debt chosen by the firm as a function of k, given b, a, z, and, again, two different levels of the signal. For the low signal case, we also compare in each panel the impact of noise σ of the signal.

Figure A.2: 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.3). 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.