Credit Markets, Learning, and the Business Cycle*

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Abstract

We argue that learning from noisy information is an important propagation mechanism for understanding credit and business cycles. First, we show that revisions of corporate profit expectations in survey data forecast changes in credit spreads and investment up to two years ahead, both in the aggregate and at the firm level. Second, we interpret these findings in a dynamic model with default risk and asymmetric information, whereby lenders are uninformed about firms' creditworthiness and optimally learn from a noisy public signal. We use the reported expectations from surveys to discipline investor expectations in the model. When the short-term profit outlook deteriorates, lenders become pessimistic about firm default risk. In turn, the firm perceives that debt is underpriced and cuts back investment. We show that: 1) the model can match the size of the credit risk premium even with risk-neutral lenders whose subjective default risk of the firm is consistently larger than the historically realized default risk; 2) the model generates counter-cyclical spreads and defaults, in sharp contrast to the counterfactual prediction of standard models with full information; 3) the mechanism can account quantitatively for the long-lasting widening in spreads and contraction in aggregate investment during the 2007-09 financial crisis.

JEL codes: E32, E44, G12, D83

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1 Introduction

Since the financial crisis of 2007-9, there has been growing aggregate evidence that credit market valuations move predictably over the credit cycle (Greenwood and Hanson, 2013) and, in turn, are tightly linked to future business cycle outcomes (Gilchrist and Zakrajšek, 2012; López-Salido, Stein, and Zakrajšek, 2017). However, we still have relatively little micro evidence on the link between credit markets and real economic outcomes, and we know little about the transmission mechanism underlying the link. This paper makes progress on both fronts, by analyzing new micro data and offering a theory of business cycles based on information frictions in credit markets.

We argue that learning from noisy information is an important propagation mechanism for understanding credit and business cycles. We start by showing that revisions of corporate profit expectations in survey data forecast changes in credit spreads and investment up to two years ahead, both in the aggregate and at the firm level. We then formally develop the mechanism by embedding rational learning by credit market investors into a dynamic model of optimal financial and investment policy for firms. There are two key frictions in the model: financial frictions that limit firms' ability to insure against shocks, and asymmetric information between firms and credit market investors, who are uninformed about firms' creditworthiness and optimally learn from a noisy public signal. We show that the interactions of the two frictions give rise a new amplification mechanism: When investors observe a deterioration in the short-term profit outlook from the signal, they become pessimistic about firm default risk. In turn, the firm perceives that debt is underpriced and cuts back investment.

We use the reported expectations from surveys to discipline investor expectations in the model, and our quantitative analysis leads to three main advances. First, the model can match the size of the credit risk premium with risk-neutral investors, whose subjective default risk of firms is consistently larger than the historically realized default risk. This arises because investors are uncertain about a low probability event such as firm default, so they demand a higher premium. Second, since time-varying investor expectations influence the effective supply of credit, the model generates counter-cyclical spreads and defaults. These dynamics are critical features of credit cycles that cannot be explained by real business cycle models with costly external finance and full information. Third, we show that fluctuations in short-term expectations can account for the long-lasting widening in spreads and contraction in aggregate investment during the 2007-09 financial crisis.

The stylized facts we document between changes in expectations of corporate profits, credits spreads, and macroeconomic aggregates utilize forecasted next quarter corporate profits between 1970 and 2010 from the Survey of Professional Forecasters (SPF) as a source of expectations. We find that 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. Moreover, by inducing time-variation in expected returns to credit market investors, short-term changes in expectations have significant forecasting power for economic aggregates including GDP growth and business investment at long horizons.

Next, we zoom into microdata to verify if a similar impact of fluctuations in investor expectations holds at the firm level. We find that a firm-level measure of short-term quarterly analyst forecast revisions between 1982 and 2010 from I/B/E/S is strongly and economically related to spreads and investment over long horizons. Importantly, the relation remains strong even after we refine identification by isolating changes or "shocks" to expectations that are plausibly unrelated to current or past macroeconomic and firm fundamentals. We construct the expectations shocks using two identification strategies. The first approach is similar to Fracassi, Petry, and Tate (2016), using analyst–specific changes in expectations that are orthogonal to realized changes in firm fundamentals. The second approach is to use a quasi-natural experiment that exploits "shocks" to 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 and macroeconomic fundamentals.

In sum, both macro- and micro-level evidence indicates that a deterioration in short-term expectations of corporate profits is a key part 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 micro-level evidence suggests that the relation is not spurious, as changes in expectations predict spreads and economic aggregates even after controlling for current or past macroeconomic and firm fundamentals. To clarify the economic mechanism behind the joint predictability of bond returns and macroeconomic aggregates, we develop a model of credit-market investors' learning.

The model is cast in a standard infinite-horizon, discrete-time stochastic environment with value-maximizing investment and financing decisions under costly external financing (see, for example, Hennessy and Whited, 2007, Gomes and Schmid, 2017). The model has two unique features: first, credit-market investors are uninformed about the firm's default risk; second, they form beliefs about it by learning from publicly-available information from professional forecasters. As investors' subjective beliefs about the default risk affect debt pricing, noisy public information can have significant impact on a firm's financial and investment policies even though the firm knows its true default probability.

For a realistic parametrization that is calibrated to match average investment, leverage, profitability, and default rates, we examine the quantitative implications of the model. In particular, with negative and volatile public information about profit outlook during the 2007-09 crisis, the model generates a persistent widening in credit spreads, which is up to three times larger than that predicted by the counterfactual model with full 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 our mechanism, which coincides with the evidence from our regression-based counterfactual. The model also boosts the volatility of investment relative to the full information benchmark.

Besides providing a new amplification mechanism, the model can replicate key stylized facts of the credit cycle more successfully than the full information benchmark. In particular, the model generates countercyclical default rates and spreads, which are both counterfactually pro-cyclical in the full information benchmark with TFP shocks. While any shock to the demand for credit makes quantities and prices move in the same direction, thereby generating procyclical spreads, changes in investors' expectations induce divergence in prices and quantities in the model. Therefore, our mechanism is an information-based credit-supply theory of business cycles. Importantly, our 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.[1]

Related Literature Our paper focuses on the link between credit markets and business cycles and is complementary to a large literature on the role of financial frictions (see Gertler and Gilchrist, 2018 for a recent survey). As in the workhorse macroeconomic models with financial frictions (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.[2] We contribute to this literature in two ways. First, we show that the interplay between financial and information frictions generates a new amplification channel via changes in expectations, rather than just changes in fundamentals. Second, we take a different and complementary approach to explain the cyclicality of credit spreads in the data, and hence the channel through which a disruption of credit markets can amplify business

[1]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).

[2]The literature has also emphasized the role of leverage and weak balance sheets, 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).

cycle fluctuations. In both the seminal paper by Bernanke, Gertler, and Gilchrist (1999) and more recent contributions such as Gertler and Karadi (2011), the "financial accelerator" operates through the balance sheets of financial intermediaries (i.e. the banking sector), who tighten their lending standards in a downturn, thereby raising the cost of borrowing for firms and amplifying the downturn. Instead of focusing on intermediated credit (loans), our credit-supply theory of the business cycle seeks to explain fluctuations in the supply of direct credit (bonds). The alternative angle is related to, and in fact motivated by, two empirical observations in the literature. First, even before the crisis, bond markets have become a significant source of financing for U.S. public firms (see, for example, Benmelech, Kumar, and Rajan, 2019). Second, there was a significant shift in the composition of credit from loans to bonds during the 2007-09 financial crisis (Becker and Ivashina, 2014; Adrian, Colla, and Shin, 2012).

This paper is related to models with changes in expectations as a source of business cycle fluctuations (e.g. Lorenzoni, 2009; Jaimovich and Rebelo, 2009; Beaudry and Portier, 2007). In our model, changes in expectations from public surveys can be interpreted as "news shocks" in credit markets. Moreover, these signals provide only a noisy forecast of the actual future profit, leaving a role for "noise shocks" in an incomplete-markets model.[3] Besides providing a mechanism through which they propagate in credit markets, we also contribute to the literature by presenting new evidence that both types of "shocks" have forecasting power for credit spreads and real activity. In doing so, we relate to the recent macro literature that uses micro data to examine the link between expectations and firm decisions (Coibion, Gorodnichenko, and Ropele, 2020; Coibion, Gorodnichenko, and Saten, 2018), and the micro evidence we contribute supports the recent empirical findings that credit spreads are tightly linked to future aggregate outcomes (Gilchrist and Zakrajšek, 2012; López-Salido, Stein, and Zakrajšek, 2017).

In exploring learning as a source of amplification and propagation in the presence of imperfect information, our paper relates to recent contributions in the learning literature, such as Eusepi and Preston (2011), Adam, Marcet, and Nicolini (2016), Adam, Marcet, and Beutel (2017), and Adam and Merkel (2019). However the mechanism for propagation is different. In these models, the propagation comes from how shifts in beliefs about future returns can affect current equilibrium prices, which in turn affect beliefs, and the key friction is the (small) deviation from rational expectations. In our model, investors

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

learn from public signals that are not affected by firms' decisions, and as these public signals may not coincide with firm fundamentals, there is a wedge between the belief of the firm and investors. And, because signals are noisy, new information gets incorporated slowly into debt prices through investors' belief updating.[4] This mechanism does not require deviation from rational expectations, but requires asymmetric information and incomplete markets.

One advantage of our rational-learning benchmark is that it can be used to quantify the relative contribution of different mechanisms that drive credit cycles, including behavioral explanations, such as extrapolative expectations (Bordalo, Gennaioli, and Shleifer, 2018, Bordalo, Gennaioli, Shleifer, and Terry, 2019, and Greenwood, Hanson, and Jin, 2019). Our model extensions that consider alternative types of learning are a first step to explore the relative importance of rational versus behavioral explanations of credit cycles. Moreover, our empirical analysis confirms the complementarity of these explanations, since changes in expectations that are orthogonal to realized changes in fundamentals still have forecasting power for spreads and investment.

Layout We begin in Section 2 by laying out some motivational evidence from aggregate data. In Section 3, we delve deeper into the micro-level data and find that it corroborates the evidence in the aggregate data. Based on the evidence, we build a firm financing model with financial and information frictions in Section 4. Section 5 illustrates our main mechanism in a simple two-period setting. Section 6 describes our parametrization strategy, followed by a discussion on the quantitative implications of the model on corporate investment and credit spreads. Section 7 shows that our model predictions are robust in a general equilibrium setting. Section 8 concludes.

2 Motivating Evidence from Aggregate Data

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

[4] As investors pool on the public information, the signals can be interpreted as credit market sentiment in the model. As such, the paper is related to the literature showing how "sentiments" – either modelled as exogenous processes (see, for example, Angeletos and La'O, 2013) or endogenous changes in beliefs (Acharya, Benhabib, and Huo, 2019) – can drive aggregate fluctuations. Under this interpretation, the model provides a novel mechanism for the time-series evidence of López-Salido, Stein, and Zakrajšek (2017).

current revision in investors' expectations of next quarter corporate profits:

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

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.

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

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

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

We report the main results in Panel A, where we measure expected risk premiums in the corporate bond market using the excess return on corporate bonds. In Panel B, we show robustness to adding controls for other predictors that have been established in the literature, which include growth in aggregate total factor productivity (Bordalo, Gennaioli, and Shleifer, 2018; Bordalo, Gennaioli, Shleifer, and Terry, 2019), the high-yield share of new bond issues (Greenwood and Hanson, 2013), the lagged corporate bond premium (López-Salido, Stein, and Zakrajšek, 2017), and a measure of equity market sentiment from Baker and Wurgler (2006).[5]

Since the measures of expectations are scaled by their respective unconditional stan-

[5]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).

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

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

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

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

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

Economic Significance In summary, aggregate evidence indicates that a deterioration in investor expectations of corporate profits tends to be followed by a subsequent widening of credit spreads, and that the timing of this widening is, in turn, closely tied to the onset of a contraction in economic activity. To provide an alternative assessment of economic significance of the effects of changes in investor expectations, we consider the 2006 to 2008 period, when revisions were revised downward by about half of a standard deviation (44%), on average, and the dispersion of revisions increased by about 3 standard deviations (see Table 1). Our first stage estimates in Table 2 imply that the combined effect of downward revisions and higher dispersion raised spreads by about 80 basis points ($0.143\times0.44+0.242\times3$), on average, in that period.

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

3 Evidence from Microdata

The previous section presents motivational evidence from aggregate data, but some caution is needed in drawing firm conclusions. The aggregate nature of the data masks differences in the composition of firms, both over time and in cross-section. For instance, we cannot distinguish firms which reduced investment and have negative revisions in profit during a recession, from firms that reduced investment but are perceived to remain profitable (i.e. without negative revisions). If the aggregate evidence were primarily driven by the second group of firms, that would imply a different mechanism driving the business cycle from the one we are proposing in this paper.

To address these justified concerns, we present more direct support for our mechanism in this section, using micro datasets that combine firm-level estimates of earning forecasts produced by financial analysts and firm-level investment and financing data.

3.1 Data Description

We use microdata to investigate the impact of fluctuations in investor expectations for U.S. public firms between 1982 and 2010. Our data sources include the I/B/E/S Detail History File (unadjusted) for analyst-by-analyst EPS forecasts, ICE/IDC and the Warga database for bond-level spreads, and quarterly Compustat for firm balance sheet information. We avoid using the off-the-shelf consensus forecast from the I/B/E/S Summary History File because it is known to be problematic due to backfilling and stale information among other issues (see, for example, Bouchaud, Kruger, Landier, and Thesmar, 2019).

Using the detailed analyst-by-analyst forecasts, we calculate the firm-level consensus EPS forecast as the median of all analysts' forecasts for the relevant period. We then construct a quarterly measure of forecast revisions at the firm level:

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

i.e. the firm-level measure is defined as the change between current and last period's forecasts of next quarter corporate profits.[6] As explained below, we also consider a residualized version of Rev_{it}, which is constructed as the analyst-specific component that is estimated after controlling for the firm-specific component of Rev_{it}.

We then merge the firm-level measure of forecast revisions with monthly bond-level spreads from ICE/IDC for 1998-2010, which has comparable coverage to the formerly available Merrill Lynch database, and from the Warga database (via Mergent FISD) for 1982-1997. As the I/B/E/S information is available starting from 1982, the resulting samples are panels of about 5,000 bonds (800 firms) and 10,000 firms between 1982 and 2010, respectively. Table 1 presents the summary statistics for the main explanatory variables over the sample period (Panel C) and for the main outcomes (Panel D).

3.2 Cross-Sectional Correlations

Cross-Sectional Correlations We start by using panel regressions to confirm that the negative (positive) time-series relation between changes in expectations of corporate profits and corporate credit spreads (investment) in the aggregate also holds in the

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

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 4, 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.

Aggregate Implication from Regression-Based Counterfactual We conduct the following counterfactual exercise to compute a back-of-the-envelope estimate for the impact of changes in expectations during the Great Recession (between 2007Q4 and 2009Q2 as per the NBER cycle dates) on aggregate investment. We compare the actual annual contraction in aggregate investment in the Great Recession to that implied by an in-sample prediction based on the regression estimate in Column (3) of Table 4. 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 (-19.8%) and the counterfactual (-15%) is about 5 percentage points, which is roughly a quarter of the overall contraction during the Great Recession.

3.3 Refining Identification Using "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. Moreover, revisions may be due to realized changes in firm fundamentals that are not controlled for. To address these issues, we use two empirical strategies. First, we refine identification by isolating changes or "shocks" to expectations, denoted by ε_{it}^{Rev}, that are unrelated to realized macroeconomic and firm fundamentals. Second, we use a quasi-natural experiment that exploits "shocks" to revisions around brokerage house mergers.

Identification Using Analyst-Specific Change in Expectations The first identification strategy is similar to Fracassi, Petry, and Tate (2016), whereby we construct a measure of "shocks" to revisions based on analyst-specific change in expectations that are plausibly independent from realized changes in firm fundamentals. The analyst-specific shocks are estimated using a regression-based decomposition method as the analyst-quarter effects in an analyst-level regression of quarterly revisions that also includes firm-quarter effects to control for (changes in) firm fundamentals. Specifically, the regression specification is given by:

$$Rev_{jit} = \alpha_{it} + \beta_{jt} Analyst_{jit} + \varepsilon_{jit}, \tag{3}$$

where Rev_{jit} is the change in expectations for firm i in quarter t by analyst j. α_{it} is a firm-quarter fixed effect. $Analyst_{jit}$ includes the explanatory variables of interest: dummy variables for each analyst j that take the value 1 if the analyst covered firm i in quarter t, and zero otherwise.

This approach makes it unnecessary to include any time-varying controls for firm fundamentals such as size and profitability, since they cannot be identified independently from the fixed effects. It also mitigates selection concerns. The matching of analysts to firms is unlikely to be random; for example, analyst teams are often organized by sector. However, the interpretation of our results is not affected by this type of matching because we compare each analyst's revisions only with those of peers who make forecasts for the same firm in the same quarter. We calculate the average of the resulting analyst-specific shocks within a given firm-quarter to construct the firm-level shock, ε_{it}^{Rev}, i.e.

$$\varepsilon_{it}^{Rev} = \frac{1}{N_{it}} \sum_{j} \hat{\beta}_{jt} Analyst_{jit} \tag{4}$$

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

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

$$Y_{it \to it+k} = \alpha + \beta \varepsilon_{it}^{Rev} + \gamma Controls_{it} + \tau_t + u_{it+k}, \tag{5}$$

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

Identification Using a Quasi-Natural Experiment The second identification strategy is to use a quasi-natural experiment that exploits variation in revisions around 15 brokerage house mergers between 1982 and 2005 that affect over 500 firms for which we have complete information on revisions. The source of 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 realized firm and macroeconomic fundamentals. To ensure that we are not capturing just changes in analyst coverage, we exclude observations involving brokerage house closures, as these events have been shown to affect the information environment and the firm incentives to produce public information (see, for example, Balakrishnan, Billings, Kelly, and Ljungqvist, 2014).

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

$$R_{it\to it+k} = \alpha + \beta Rev_{it} + \gamma Controls_{it} + \tau_t + u_{it+k}, \tag{6}$$

with $k = 4{,}8$ respectively. As above, firm-level controls include firm size and current profitability, and τ_t denotes time fixed effects. To assess the impact on firm investment, we regress investment on the predictable component of excess bond returns from (6), $R_{it\to it+k}$. The results are reported in Columns (9)-(10) of Table 4.

Discussion The estimates for spreads and investment remain large and strongly statistically significant under both approaches. Such evidence helps to distinguish our mechanism from other macro theories because it shows that changes in expectations matter for spreads and investment even after we control for aggregate shocks by including time effects and for realized changes in firm fundamentals.

Furthermore, the evidence also helps to distinguish our mechanism from behavioral theories of the credit cycle that emphasize diagnostic expectations (e.g., Bordalo, Gennaioli, and Shleifer, 2018, Bordalo, Gennaioli, Shleifer, and Terry, 2019). In these theories, though changes in expectations amplify the cycle, the ultimate driving forces of the cycle remain realized changes in fundamentals. As such, the evidence that even after controlling for changes in fundamentals there is an independent role for expectations, indicates that learning and diagnostic expectations are distinct and complementary mechanisms.

3.4 Additional Supporting Evidence

Lastly, Table 5 uses sample-split analysis to offer additional supporting evidence. We regress changes in spreads and investment on a "Crisis$_t$" indicator that is equal to one between 2007Q4 and 2009Q2:

$$\Delta R_{it} = \alpha + \beta Crisis_t + \gamma Controls_{it} + u_{it}. \tag{7}$$

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

Second, we further stratify the sample based on whether firms with the most negative revisions also had their debt rated as junk (triple B or lower, Column (3)). Third and final, we consider a sub-sample of firms where analysts are most reliant on public signal (Column (4)). Based on our model, these firms should be most sensitive to macro conditions. To measure reliance on public signal, we follow Chen and Jiang (2006) and use analyst-level regressions to calculate for each analyst the correlation between forecast errors[7] 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.

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[7]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.

4 A Firm Financing Model with Incomplete Information

Motivated by our empirical results, we now build a firm financing model with endogenous default and incomplete information with learning by debt investors.[8] The firm can finance investment either internally through accumulated earnings or externally through debt and equity. 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.

In addition to the standard financial frictions, we consider asymmetric information in debt markets. This is the key innovation of the model. Specifically, we assume that bond investors know the structure of the economy but they cannot observe some latent state of the firm. Instead, investors form beliefs about it using publicly-available information from survey data. In what follows, we provide a framework to study how rational learning from noisy signals can affect bond spreads as well as firm leverage and investment decisions. The framework can be extended along several dimensions, one of which is shown in Section 7.

4.1 Economic Environment

A. Technology and Income Processes

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

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

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

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

[8]As discussed in the previous section, the purpose of using micro data is primarily for estimating "shocks" to expectations after controlling for changes in firm fundamentals, rather than for drawing cross-sectional implications. Therefore, to main tractability and keep focus on the new amplification channel, we build a representative-firm model here, and it can be extended into a heterogeneous-firm model if one is interested in drawing cross-sectional implications.

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

$$\log a' = \rho_a \log a + \varepsilon'_a \tag{8}$$

$$z' = \mu_z + \rho_z z + \varepsilon'_z, \tag{9}$$

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. Since both are aggregate shocks and there are no idiosyncratic shocks, we will concentrate on the symmetric equilibrium where all firms are alike (representative firm).[9] Capital accumulation follows:

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

subject to a quadratic investment adjustment cost:

$$g(k,k') = \frac{c_k}{2}\Big(\frac{k' - (1-\delta)k}{k}\Big)^2 k. \tag{10}$$

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 $\xi \in (0,1]$.

[9] The assumption that investors cannot observe all aggregate shocks is not necessary for our mechanism in a more general setting. For instance, in a heterogeneous-firm setting where firms can observe both aggregate and idiosyncratic shocks but investors can only observe the aggregate shock, our mechanism would also go through.

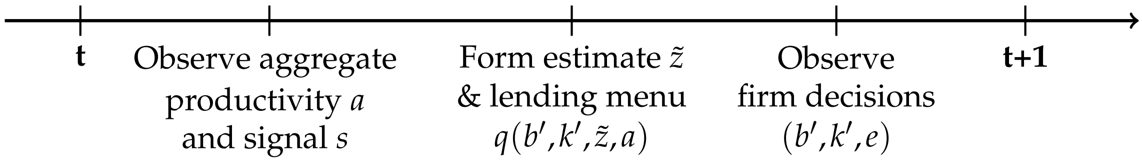

Figure 1: Timing of the investors' problem

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:

$$\Lambda(e) = 1_{e<0} c_e e \tag{11}$$

where $1_{e<0}$ is an indicator variable that equals to 1 if $e < 0$ and 0 otherwise.[10]

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 (9), 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:[11]

$$s = \rho_s s_{-1} - \varepsilon_z + u. \tag{12}$$

The noise in the signal, u, is i.i.d. normal with zero mean and variance σ_u^2. ε_z and u independent.

Figure 1 shows the timing of investors' problem. After observing s, investors can use the laws of motion for z (9) and s (12) to form an estimate of z (denoted by $\tilde{z}$) using the following relation:

$$\tilde{z}(\mathcal{S}) = \mathrm{E}\left[z|\mathcal{S}\right] = \frac{\mu_z}{1-\rho_z} - \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_u^2} \sum_{j=0}^{\infty} \rho_z^j \left(s_{-j} - \rho_s s_{-j-1}\right), \tag{13}$$

given the history of s up to the current period, $\mathcal{S} = \{s_0, s_1, ..., s\}$. Hence the information set of debt investors at time t includes the history of all the model variables through

[10] 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.

[11] We use this process to fit the data (see Section 6). 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 $\rho_z > 0$.

time t but not the current and past realizations of ε_z (see Appendix A for details). Given their estimate $\tilde{z}$ and observed aggregate productivity a, debt investors form this period's "lending menu" $q(b',k',\tilde{z},a)$, consisting of the prices of defaultable bonds for different levels of bond issues b' and capital k'. We discuss how these prices are determined in Section 4.3.

4.2 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:

$$J(k',b',z'^{*},a',\tilde{z}') = 0 \tag{14}$$

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):

$$\begin{aligned} J(k,b,z,a,\tilde{z}) = \max \Bigg[0, \; & \underbrace{(1-\tau)\big(ak^{\alpha}-z\big)}_{\text{after-tax profit}} - \underbrace{(c+\lambda)b}_{\text{debt payment}} + \underbrace{\tau\big(\delta k + cb\big)}_{\text{tax rebate}} \\ & + \underbrace{V(k,b,z,a,\tilde{z})}_{\text{continuation value}} \Bigg], \end{aligned} \tag{15}$$

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

$$\begin{aligned} V(k,b,z,a,\tilde{z}) = \max_{b',k',e} \Bigg\{ & \underbrace{q(b',k',\tilde{z},a)\Big(b' - (1-\lambda)b\Big)}_{\text{value of new debt issues}} - \underbrace{\Big(k' - (1-\delta)k\Big) - g(k,k')}_{\text{investment and adj. cost}} \\ & \underbrace{+\Lambda(e)}_{\text{equity issuance cost (11)}} \\ & \underbrace{+\beta \int_{\underline{a}}^{\overline{a}} \int_{\underline{z}}^{\overline{z}} \int_{\underline{z}}^{z'^{*}(k',b',a',\tilde{z}')} J\big(k',b',z',a',\tilde{z}'\big) \;\; P(z,dz')P(\tilde{z},d\tilde{z}')Q(a,da')}_{\text{expected future equity value}} \Bigg\}. \end{aligned} \tag{16}$$

The definition of equity payout / issuance is given by:

$$\begin{aligned} e = (1-\tau)\big(ak^{\alpha}-z\big) - \big(c+\lambda\big)b - \big(k' - (1-\delta)k\big) - g\big(k,k'\big) \\ +\tau\big(\delta k + cb\big) + q(b',k',\tilde{z},a)\Big(b' - (1-\lambda)b\Big), \end{aligned} \tag{17}$$

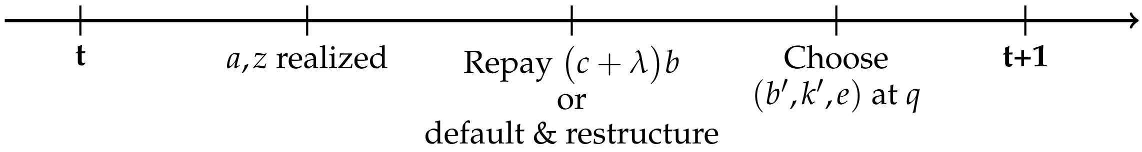

Figure 2: Timing of the firm's problem

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, $\big(c+\lambda\big)b$. If the equity value $J(\cdot)$ is positive, the firm repays, distributes dividends, and decides on its investment and financing decisions for the next period. Otherwise, the shareholders walk away from the firm, and investors take over and restructure it. After restructuring, investors sell off the equity portion to new owners, who then choose b', k', and e, and the firm resumes operation.[12]

Bond investors observe a and s when the firm observes a and z. Investors form their estimate of the firm's latent state $\tilde{z}$ according to (13). 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.

4.3 Pricing of Corporate Bonds

The price of bond b' raised in t follows the no-arbitrage condition:[13]

$$\begin{aligned}
&q(b',k',\tilde{z},a)\\
&\quad=\beta\Bigg\{\int_{\underline{a}}^{\overline{a}}\int_{\underline{z}}^{\overline{z}}\int_{\underline{z}}^{\tilde{z}'^{*}(k',b',a',\tilde{z}')}\Big[c+\lambda+(1-\lambda)q'(b'',k'',\tilde{z}',a')\Big]P(\tilde{z},dz')P(\tilde{z},d\tilde{z}')Q(a,da')\\
&\qquad\quad+\int_{\underline{a}}^{\overline{a}}\int_{\underline{z}}^{\overline{z}}\int_{\tilde{z}^{*}(k',b',a',\tilde{z}')}^{\overline{z}}B(b',k',z',a',\tilde{z}')\;\;P(\tilde{z},dz')P(\tilde{z},d\tilde{z}')Q(a,da')\Bigg\}. \qquad (18)
\end{aligned}$$

[12]In other words, default is followed by restructuring (subject to a deadweight loss) and not firm exit in the model. This assumption follows Gomes, Jermann, and Schmid (2016), as a way to enhance tractability, since entry and exit are not crucial for our mechanism here.

[13]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.

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 $B_{\max}$:

$$B(b',k',z',a',\tilde{z}') = \min\Bigg[\max\Big[0,\ \Big((1-\tau)\big(a'k'^{\alpha}-z'\big) + V(k',b',z',a',\tilde{z}') + (1-\lambda)q'(b'',k'',\tilde{z}',a')b' - \xi k'\Big)\frac{1}{b'}\Big],\ B^{\max}\Bigg]. \tag{19}$$

4.4 Recursive Competitive Equilibrium

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

1. $b'(b,k,z,a,\tilde{z})$, $k'(b,k,z,a,\tilde{z})$, e, $J(b,k,z,a,\tilde{z})$, and $V(b,k,z,a,\tilde{z})$ satisfy the firm's optimization problem (15) and (16), given the bond pricing schedule $q(b',k',\tilde{z},a)$;

2. $q(b',k',\tilde{z},a)$ satisfies the break-even condition (18) subject to (13) and (19), given the law of motion for the signal (12), and the history of signals $\mathcal{S} = \{s_0,s_1,...,s\}$.

5 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.

5.1 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:

$$\begin{aligned} q_t &= \beta \mathrm{E}_t \left[p_{t+1} + \tilde{B}(1 - p_{t+1}) \middle| s_t \right] \\ &= \beta \Big(\tilde{B} + \big(1 - \tilde{B}\big) \mathrm{E}_t \left[p_{t+1} \middle| s_t \right] \Big) \\ &= \beta \left(\tilde{B} + \big(1 - \tilde{B}\big) \left[\bar{p} + \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_u^2} s_t \right] \right). \end{aligned} \tag{20}$$

If the investors are risk-neutral, the spread between the risky bond and the risk-free bond is given by:[14]

$$\begin{aligned} \tilde{R}_{t+1} &= \mathrm{E}_t \left[1 - x_{t+1} \middle| s_t \right] \\ &= \Big(1 - \mathrm{E}_t \left[p_{t+1} \middle| s_t \right] \Big) \big(1 - \tilde{B}\big) \\ &= \left(1 - \left[\bar{p} + \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_u^2} s_t \right] \right) \big(1 - \tilde{B}\big) \\ &= \underbrace{(1 - \bar{p})\big(1 - \tilde{B}\big)}_{\text{default premium}} - \underbrace{\frac{\sigma_\varepsilon^2 \big(1 - \tilde{B}\big)}{\sigma_\varepsilon^2 + \sigma_u^2} s_t}_{\text{learning}} \end{aligned} \tag{21}$$

Therefore, equation (21) 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

[14]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.

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 (21) that the volatility of spread is increasing in the volatility of the signal.

5.2 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}:

$$q_t = \beta\Big(\tilde{B} + \big(1 - \tilde{B}\big)p_{t+1}\Big). \tag{22}$$

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 4), 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 3.

In technology-driven real business cycle models with costly external finance and endogenous default, empirically plausible parameterization often leads to procyclical credit spreads. This result runs counter to the data, as discussed by 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 (20) 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 3.

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

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

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

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

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

6 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.

6.1 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 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 4 plots this series from the Survey of Professional Forecasters between 1970Q1 and 2010Q4. We determine σ_u using the following relation:

$$\sigma_u^2 = (1 - \rho_s^2)\sigma_s^2 - \sigma_\varepsilon^2 \tag{23}$$

which comes from equation (12), 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. $s_t = \ln \mathrm{E}_t(\Pi_{t+1}) - \ln \mathrm{E}_{t-1}(\Pi_{t+1})$.[15] We estimate an AR(1) process for s_t to obtain estimates for σ_s and ρ_s in (12). Then, with the estimates for σ_s and σ_ε, we use relation (23) to compute the volatility of noise σ_u.

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, and the algorithm is laid out

[15]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.

in Appendix C. To find $\{\xi, \mu_z, c_e, c_k\}$, we generate simulated data that is comparable to Compustat. Specifically, we simulate the model for 1,000 quarters and keep the last 100 quarters to compute the model-implied moments, as this corresponds to the time span of our Compustat sample. We repeat this 5,000 times and take the average.[16] The parameter values in the baseline model with rational learning are summarized in Table 6.

6.2 Model Fit

Table 7 presents the model predictions of the aggregate moments and their data counterparts. Panel A presents the targeted moments, and Panel B shows the non-targeted moments for credit spreads, default rates, and investment. The baseline model with imperfect information is able to capture the countercyclical default rates and credit spreads, and it can generate a reasonable level of spread despite the low default rate associated with the long-term debt. Moreover, the model can generate countercyclical spreads without imposing time-varying default costs or introducing other types of aggregate shock.

We also conduct an "event study", as shown in Figure 6, to examine the model-implied credit spreads during the period. In this exercise, we simulate the two models (with and without information frictions) by feeding in the actual shocks to measured TFP (a), the actual shocks to the cost of operation (z), and the revision series (s), together with the policy functions and parameters in Table 6, except for ρ_s and σ_u. In this exercise, we estimate the learning parameters using an expanding window and feed them into the model period-by-period: 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 $\mathcal{S} = \{s_0, s_1, ..., s\}$.[17] Figure 6 shows that our baseline model with asymmetric information 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 8. Consistent with the data, short-term changes in expectations have significant forecasting power for the model-implied spread. For instance, a one standard deviation increase in revisions lowers the one-quarter ahead model-implied spread by about 20 basis points (Panel A).

[16] In other words, we create 5,000 independently and identically distributed firms.

[17] To clarify, there is no parameter uncertainty in the model (i.e. agents know them and treat them as fixed), whereas econometricians use an expanding window of the signal series s_t to estimate σ_u and ρ_s. Table A.3 reports the empirical estimates of ρ_s and σ_u for each quarter between 1985Q1 and 2010Q4. For robustness, we also repeat the event study using the values for ρ_s and σ_u in Table 6. The simulation results are presented in Figure A.2.

By influencing external finance premiums, changes in investor expectations of corporate profits also have significant forecasting power for investment and output (Panel B).

6.3 Effects of Information Frictions

Columns (2) and (3) of Table 7 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.[18] In our event study (Figure 6), we also examine the model-implied credit spreads in the counterfactual model.

We show that informational inefficiencies in the debt markets have three main effects on corporate bond spreads. First, spreads are significantly lower in the counterfactual 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, when investors are uncertain about a low probability event such as firm default, they demand higher premia.[19] In addition, "noisier" signals (with higher σ_u) increased the spread further during the 2007-09 financial crisis (see Table A.3). While these effects are absent in the counterfactual model, it allows our baseline 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. Figure 6 shows that the volatilities of spreads in the counterfactual model are more or less constant over the sample period – i.e., the volatilities in the 1980s are of a similar degree to the volatilities in 2008 – which is not the case in the data. By contrast, the 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 4). The model with information frictions captures the time variation in bond spreads as investors learn from a cyclical series s and update their estimate of the latent variable $\tilde{z}$, which in turn affects the price of bonds according to equation (18).

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 7, both spreads and default rates are procyclical in the

[18]See Appendix D for the setup of the full information model.

[19]This result comes from Jensen's inequality. See Appendix B for a proof.

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 3, 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 dominates the leverage effect on the equilibrium price of debt, because the signals are not only procyclical, but also more volatile in crisis (see Figure 4).[20]

Economic significance of noisy signals As shown in Figure 4, the revision series was very volatile during the crisis period. To investigate the economic significance of learning from noisy signals, we conduct 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 for the crisis period, we replace the original signal series with the pre-crisis average. Subsequently, we compute the average spread and annualized change in investment during the crisis, and compare them to their counterparts in the baseline model. As reported in Panel C of Table 7, in this experiment, the average spread is around 2 percentage points lower during the crisis, and the contraction in investment is 23 percent less.[21] This is very comparable to the estimate (25%) from our regression-based counterfactual (see Section 3.2).

6.4 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.

[20]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).

[21]Note that the spreads without noisy signals are still higher than the spreads implied by a model with full information, as shown in Figure 6. 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.

Table 9 compares the aggregate moments in our baseline model (low noise-low leverage) and three counterfactual exercises (high noise-low leverage, high noise-high leverage, low noise-high leverage).

Comparing the baseline (column 1) and the first counterfactual model (column 2), we see that, ceteris paribus, having noisier signals leads to higher spreads and lower investment, and the standard deviations of both variables increase. Investment decreases as the firm borrows less when the cost of borrowing is higher. The impact on default risk is the result of two forces: the cost of borrowing and the level of indebtedness. Given the parameterization, the effect of a lower leverage dominates, and the average default rate is lower in the counterfactual model.

In the second counterfactual model (column 3), we find that noisier signals lead to a bigger increase in credit spreads when the firm is more leveraged. Unlike the first counterfactual exercise, the default rate is unambiguously higher. Now the firm switches from equity financing to bond financing in the face of higher equity issuance costs. Nonetheless, under the given calibration, the increase in debt financing is less than the reduction in equity financing in equilibrium, as the firm endogenizes the increase in borrowing costs. As a result, there is less external financing in total and aggregate investment is lower.

Comparing across Table 9, we see that higher leverage implies higher credit spreads ($2.8 - 1.7 = 1.1$ percentage points), but the additional impact of having noisier signals is stronger ($4.6 - 2.8 = 1.8$ percentage points). Similarly, the decline in investment due to noisier signals ($1.5 - 2.1 = -0.6$ percentage points) is larger than the decline due to more expensive external financing alone ($2.1 - 2.4 = -0.3$ percentage points). These comparative static exercises suggest that there is an important interaction effect between financial frictions and incomplete information: noisier signals have a larger effect on credit spreads and real activity when the corporate sector is more leveraged.

6.5 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 E, 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.

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 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:

$$
\begin{aligned}
V^H(k,b,a,\tilde{z},z) = & \max_{C,h} \ u(C,h) \\
& + \beta \int_{\underline{a}}^{\overline{a}} \int_{\underline{z}}^{\overline{z}} \int_{\underline{z}}^{\overline{z}} V^H(k',b',a',\tilde{z}',z')P(z,dz')P(\tilde{z},d\tilde{z}')Q(a,da') \\
\text{s.t.} \qquad & C \leq wh + s + e + T. \qquad (24)
\end{aligned}
$$

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 4 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 (16) 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 (13). 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 (18).

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

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

respectively. In the aggregate resource constraint, recall that $g(k',k)$ is the investment adjustment cost (10), $\Lambda(e)$ is the equity issuance cost (11), and z is the cost of operation (9). $\tilde{R}^b$ 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.[22] 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 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.

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

8 Conclusion

In order to better understand the consequences of information imperfections in debt markets, we have combined macro and micro data on professional forecasts of corporate profits, bond returns, and corporate investment with a novel model of credit cycles with learning. Consistent with the idea that debt investors form beliefs about firms' creditworthiness using publicly-available information on short-term corporate profits, we have documented that changes in quarter-ahead professional forecasts of corporate profits have strong predictive power for credit spreads and investment over long horizons, both in the aggregate and at the firm level. Second, and perhaps more important as a contribution, we have developed a quantitative model that incorporates this mechanism and shown that its ability to account for key stylized facts of the credit cycles is superior to the rational learning benchmark. As such, we show that learning from noisy information is an important propagation mechanism for understanding credit and business cycles.

There are several venues along which our approach can be extended. First, motivated by the strong evidence of predictability in debt markets of Greenwood and Hanson (2013), we have focused on informational inefficiencies in debt markets. While predictability is relatively weaker in equity markets, it would be interesting to add agency issues in equity markets and explore whether they reinforce our mechanism. Second, an advantage of our quantitative model is that it can be readily extended for policy evaluation of alternative financial stability tools. Such an extension would allow for quantitative and welfare evaluation of policy counterfactuals of the effectiveness of monetary policy or other policy measures aimed at stabilizing financial markets in times of stress. Finally, our framework could be extended to study in more detail additional forces that may lead to fragility in credit markets, including, for example, relative-performance evaluation type features in institutional investors' compensation contracts (Feroli, Kashyap, Schoenholtz, and Shin, 2014).

While we look forward to these extensions, we believe that the approach developed in this paper offers a useful first take on informational inefficiencies in debt markets, which had not yet been the subject of formal analysis and testing despite the fact that learning is a central idea in modern financial economics.

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

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

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

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

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

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

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

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

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

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

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

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

Panel A: Excess Return on Corporate Bonds

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

Panel B: Robustness to Controlling for Other Mechanisms

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

Panel C: Robustness to Orthogonalizing Rev_t by

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

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

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

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

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

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

Table 4: Evidence from Microdata:
Expectations of Corporate Profits, Credit Spreads, and Investment

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

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

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

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

Table 5: Additional Supporting Evidence

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

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

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

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

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

Table 6: Baseline Parameterization

Parameter	**Description**	**Target**
Preferences and technology		
$\alpha = 0.65$	Returns to scale	Hennessy and Whited (2007)
$\delta = 0.025$	Depreciation rate	NIPA depreciation
$\beta = 0.99$	Time preference	Annual risk-free rate 4%
$c_k = 0.658$	Adjustment cost	Mean investment rate
$\mu_z = 18.36$	Mean cash flow	Mean profit-to-asset
$\rho_z = 0.966$	Cash flow persist.	Cost of goods sold
$\sigma_\varepsilon = 0.0293$	Cash flow vol.	Cost of goods sold
$\rho_a = 0.97$	Agg. productivity persist.	US quarterly GDP
$\sigma_a = 0.007$	Agg. productivity vol.	US quarterly GDP
External financing		
$\tau = 0.3$	Corporate tax rate	Graham (2003)
$\xi = 0.24$	Bankrupty cost	Mean default rate
$c = 0.0101$	Coupon rate	Price of default-free debt
$\lambda = 0.05$	Debt amortization rate	Average debt maturity
$c_e = 0.164$	Equity issuance cost	Mean leverage ratio
$B^{\max} = 0.69$	Maximum recovery rate	Top decile recovery rate
Learning		
$\rho_s = 0.264$	Persistence of signal	Revision in expected profit
$\sigma_u = 0.048$	Volatility of noise in signal	Revision in expected profit

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

Table 7: Model Fit

Panel A: Targeted moments	**Data** (1)	**Model** (2)	**Full information model** (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** (1)	**Model** (2)	**Full information model** (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 (18) 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 our event study. We also consider two models in this exercise: one is the the baseline model, and the other is a counterfactual model in which we replace the actual revisions during crisis with the pre-crisis average.

Table 8: 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 for our event study (as shown in Figure 6). 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 9: Role of Leverage and "Noisier" Signals

	Baseline	**Counterfactuals**		
	(1)	(2)	(3)	(4)
	$[\sigma_u,\ c_e]$	$[2\sigma_u,\ c_e]$	$[2\sigma_u,\ 2c_e]$	$[\sigma_u,\ 2c_e]$
First moments				
Default rate	0.010	0.007	0.020	0.024
Bond spread	0.017	0.031	0.046	0.028
Leverage	0.309	0.255	0.310	0.374
Investment	0.024	0.017	0.015	0.021
Second moments				
Corr(default, output)	−0.17	−0.22	−0.24	−0.15
Corr(spread, output)	−0.31	−0.26	−0.23	−0.28
Corr(invest, output)	0.74	0.63	0.66	0.68
σ(spread)/σ(output)	2.58	3.52	3.65	2.71
σ(invest)/σ(output)	2.75	2.96	3.11	2.86

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

Table 10: Model Fit: GE Extension

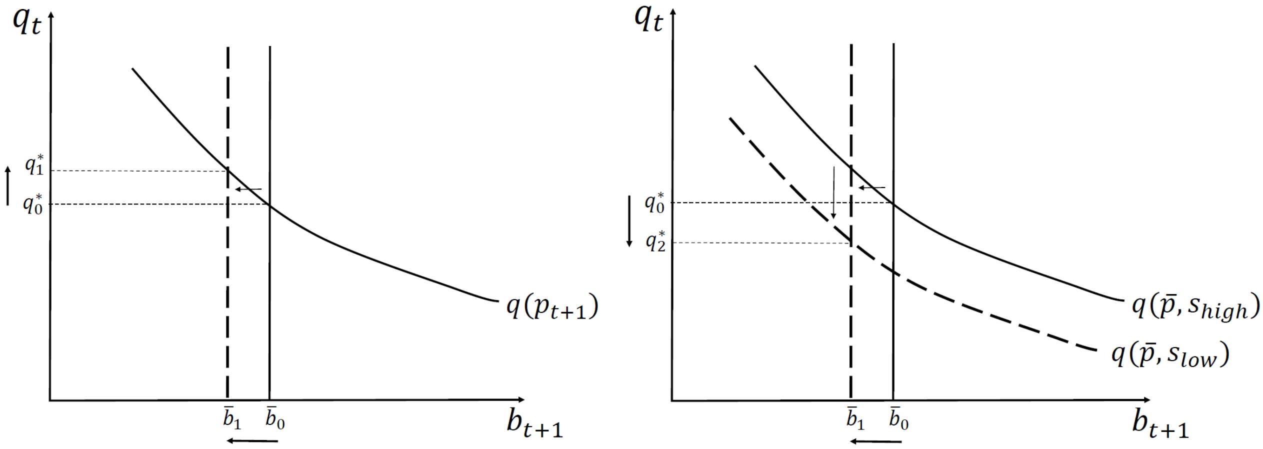
Panel A: Targeted moments	**Data** (1)	**Model** (2)	**Full information model** (3)
Investment rate (mean)	0.018	0.022	0.025
Leverage (mean)	0.267	0.291	0.298
Profit to asset (mean)	0.053	0.047	0.050
Default rate (mean)	0.013	0.007	0.009

Panel B: Untargeted moments	**Data** (1)	**Model** (2)	**Full information model** (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 3: Comparing bond market equilibrium in models with and without information frictions

(a) Perfect information model **(b)** Model with 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:

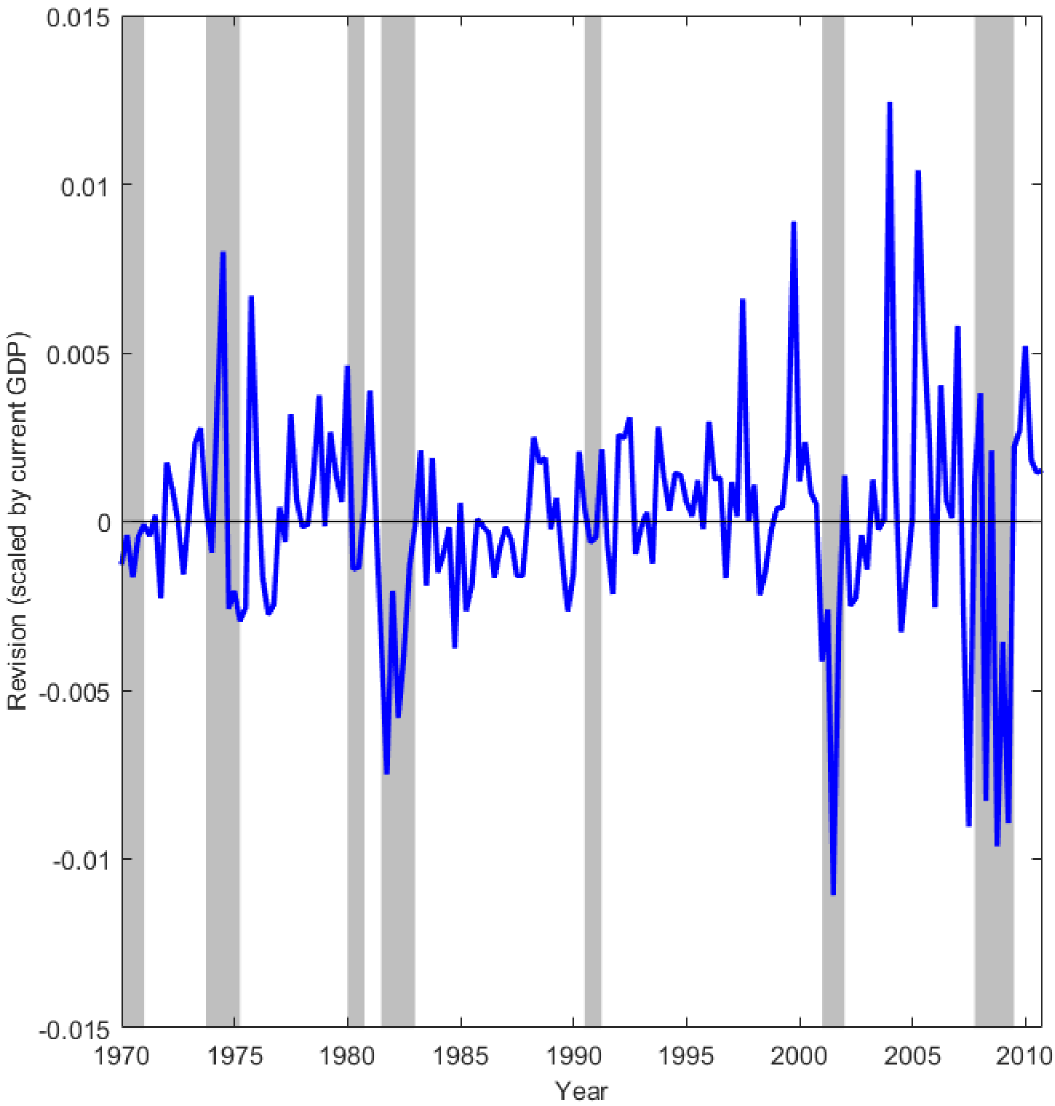
$$q_t = \beta\Big(\tilde{B} + (1-\tilde{B})p_{t+1}\Big).$$

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:

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

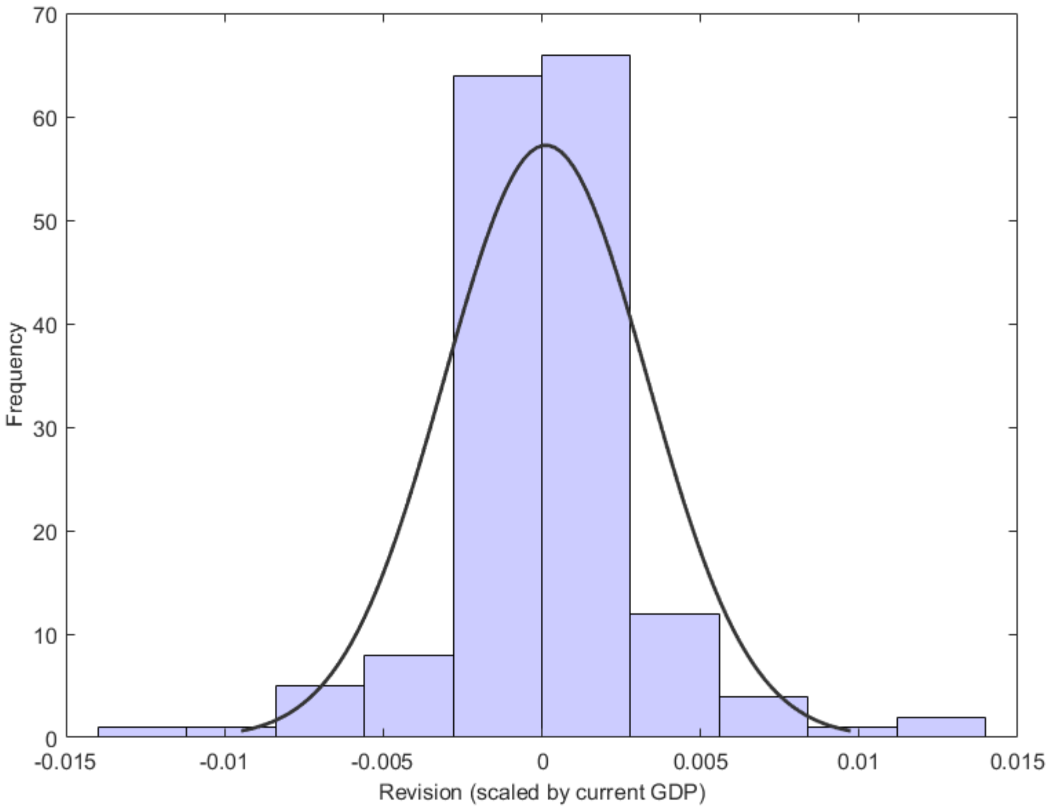
Therefore, in addition to the reduction of firm borrowing from $\bar{b}_0$ to $\bar{b}_1$, investors receive a more pessimistic signal about the firm's credit worthiness in a recession, so the demand curve shifts down from $q(\bar{p}, s_{\text{high}})$ to $q(\bar{p}, s_{\text{low}})$.

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



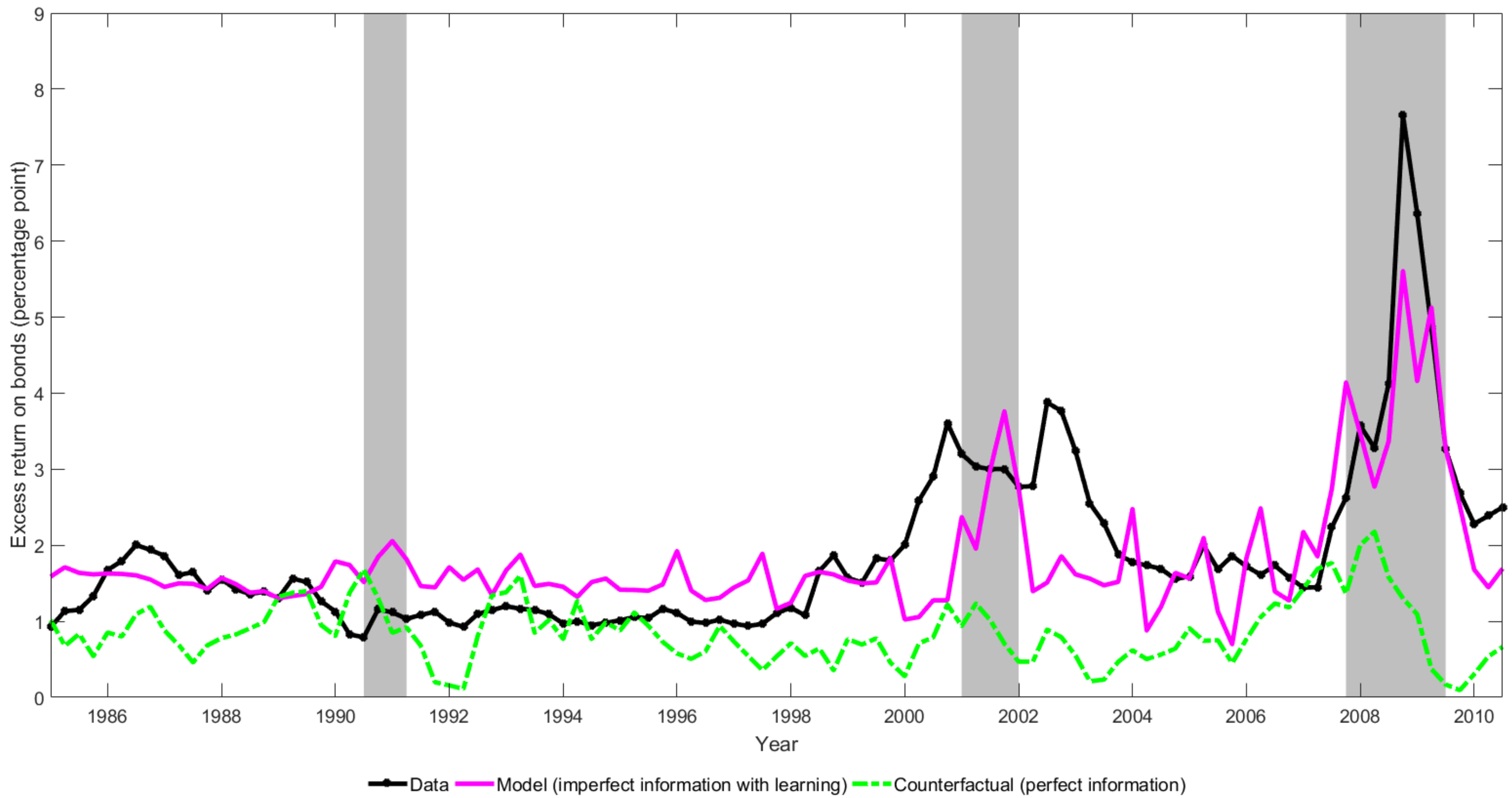
Note: This figure shows the current revision in investors' expectations of next quarter's corporate profit between 1970Q1 and 2010Q4, divided by the US GDP. Data is from the Survey of Professional Forecasters. Shaded areas indicate the NBER recession dates.

Figure 5: Distribution of the Revision Series



Note: This histogram shows the distribution of the signal – the current revision in investors' expectations of next quarter's corporate profit as a fraction of US GDP – between 1970Q1 and 2010Q4. Data is from the Survey of Professional Forecasters. The Kolmogorov-Smirnov test statistic for the sample has a p-value of 0.238.

Figure 6: 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). In this exercise, we feed in the actual shocks to measured TFP (a), the actual shocks to the cost of operation (z), and the revision series (s). Moreover, we estimate the learning parameters using an expanding window and feed them into the model period-by-period (see Table A.3): 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 $\mathcal{S} = \{s_0, s_1, ..., s\}$. Shaded areas indicate the NBER recession dates.

Credit Markets, Learning, and the Business Cycle
Online Appendix

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April 2020

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

Define $\tilde{s}_t \equiv s_t - \rho_s s_{t-1}$, and equation (12) 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 (9) 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 (13).

B Expected default probability under uncertainty

This section provides a proof for one of the quantitative implications of the model - that when investors are uncertain about a low probability event such as firm default, they put more weight on it.

In our setup, the firm's actual default probability depends on one of its state variables z. Let z^* be the default threshold such that if $z < z^*$, the firm defaults. In what follows, for illustration, we simplify the original setup in the following ways:

- $z \sim iidN(\mu_z, \sigma_z^2)$ with cdf $F(\cdot)$ and pdf $f(\cdot)$, so the firm's actual default probability is given by $P(z < z^*)$;
- the firm knows the default threshold z^*, but investors do not know;[23]
- instead, investors observe $s = z^* + \sigma\varepsilon$ with $\varepsilon \sim iidN(0,1)$, so their estimate of the firm's default probability is $P(z - \sigma\varepsilon < z^*)$.

The Lemma below gives the condition under which $P(z - \sigma\varepsilon < z^*) > P(z < z^*)$, i.e. investors attach more probability to firm default than the actual probability.

Lemma. *If $f'(z^* + \sigma\varepsilon) > 0\ \forall\varepsilon$, then $P(z - \sigma\varepsilon < z^*) > P(z < z^*)$.*

Proof. Using the Law of Iterated Expectations and Jensen's Inequality,

$$\begin{aligned} F(z^* + \sigma\varepsilon) = P(z - \sigma\varepsilon < z^*) &= \mathrm{E}_\varepsilon\Big(P(z - \sigma\varepsilon < z^*)\Big|\varepsilon\Big) \\ &= \mathrm{E}_\varepsilon\Big(F(z^* + \sigma\varepsilon)\Big) \\ &> F\Big(\mathrm{E}_\varepsilon(z^* + \sigma\varepsilon)\Big) = F(z^*) = P(z < z^*), \end{aligned}$$

since $\mathrm{E}(\varepsilon) = 0$. The inequality holds if $F(z^* + \sigma\varepsilon)$ is convex for all ε, i.e. if

$$\begin{aligned} \frac{\partial}{\partial\varepsilon}F(z^* + \sigma\varepsilon) &= \sigma f(z^* + \sigma\varepsilon) > 0; \\ \frac{\partial^2}{\partial^2\varepsilon}F(z^* + \sigma\varepsilon) &= \sigma^2 f'(z^* + \sigma\varepsilon) > 0. \end{aligned}$$

The second derivative satisfied if $f'(z^* + \sigma\varepsilon) > 0\ \forall\varepsilon$. ■

If $P(z - \sigma\varepsilon < z^*) > P(z < z^*)\ \forall\varepsilon$, investors with imperfect information demand a higher premium to compensate for the risk of default than they would if they can observe z perfectly. This would lead to higher credit spreads in the model with imperfect information. In our quantitative exercise, we find that that this is indeed the case. Intuitively this is because default is a low probability event in the model, so we are nearly always at the increasing part of the pdf $f(z^* + \sigma\varepsilon)$.

[23] For illustration, this assumption captures the idea that only the firm knows its true default probability $F(z^*)$.

C Computation

We transform (8) and (9) 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. 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 (15), 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 (17), and equity issuance cost $\Lambda\big(e_0(k, b, z, a, \tilde{z}, b', k')\big)$ using (11);

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 (16) – subject to the default threshold (14) – 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 (18):

   - 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 (19);
   - 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 $q_1(b', k', \tilde{z}, a)$;

7. Repeat steps 2–6 until convergence, i.e. the following conditions are jointly satisfied, for $\varepsilon \approx 0$:

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

D Model with Perfect Information

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

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

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 $B_{\max}$:

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

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:

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

where

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

subject to (11), (14), and the definition of equity payout / issuance:

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

E 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 (13). 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 (18), 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.[24] 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 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:

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

where $\tilde{z}$ is from the rational learning model, as defined in (13), 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 6). In addition, we perform

[24] 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).

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 (12) to be $\rho_s^B > \rho_s$, and use ρ_s^B in forming their estimate of z according to the updating equation (13). Let the difference $\zeta = \rho_s^B - \rho_s$ measure the degree of overextrapolation. We perform comparative statics analysis by calibrating two different values for ζ in turn, while keeping the other parameter values the same as in the baseline model with rational learning (Table 6). We use empirical estimates of overextrapolation from Landier, Ma, and Thesmar (2019) to calibrate ζ.[25]

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. More-

[25]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.

over, 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.

F 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		
$\rho_s = 0.264$	Persistence of signal	Revision in expected profit
$\sigma_u = 0.048$	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		
$\rho_s = 0.264$	Persistence of signal	Revision in expected profit
$\sigma_u = 0.048$	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		
$\rho_s = 0.264$	Persistence of signal	Revision in expected profit
$\sigma_u = 0.048$	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.8: Robustness Check:
Model without Equity Financing

	Data	**Baseline**	**Without equity**
	(1)	(2)	(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.

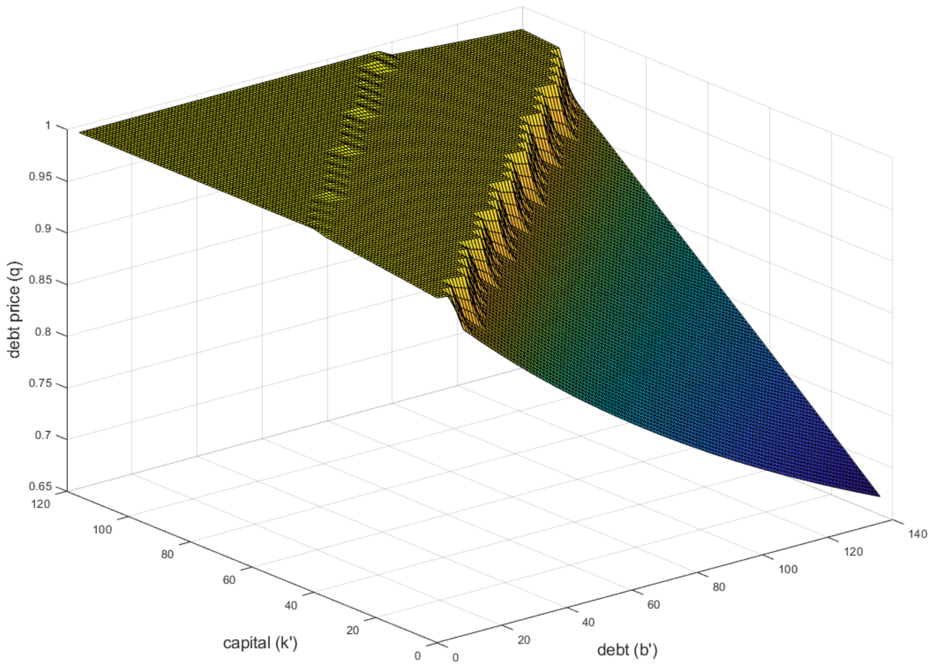
Table A.7: Aggregate Moments with Alternative Learning Rules

	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

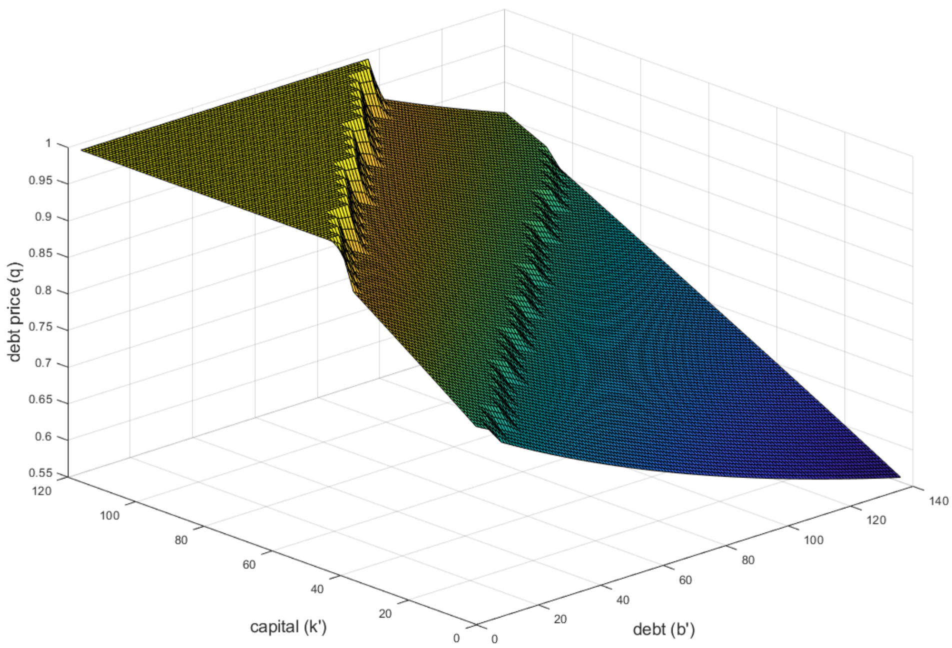
Note: This table presents the aggregate moments in the alternative learning models with biased beliefs. Columns 1 and 2 show the aggregate data moments and their model counterparts in the baseline model with rational learning. Columns 3 and 4 show the model predictions with "pessimistic" and "optimistic" 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 6.

Figure A.1: Debt Pricing Function $q(b', k', \tilde{z}, a)$

(a) $q(b', k', \tilde{z}_{\text{good}}, a)$

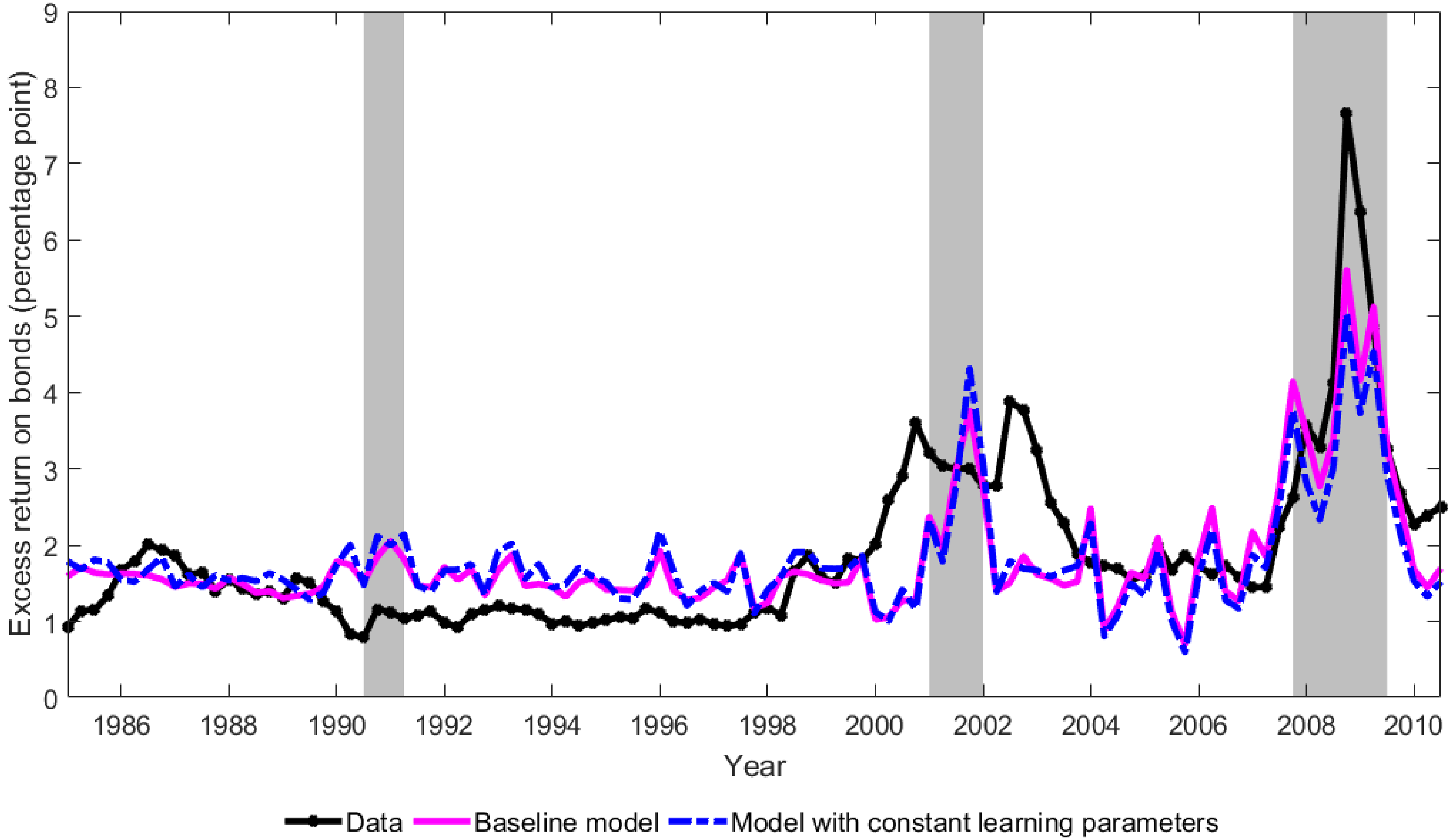


(b) $q(b', k', \tilde{z}_{\text{bad}}, a)$



Note: This table shows the debt pricing function $q(b', k', \tilde{z}, a)$ in the baseline model (section 4) with asymmetric information and rational learning. In panel (a), investors perceive the latent state to be "good" (i.e. they believe that z is low and firm profit is high), whereas in panel (b) they perceive the latent state to be "bad" (they believe that z is high and firm profit is low). Importantly, the debt pricing function is a function of investors' perceived z (denoted by $\tilde{z}$), but not the actual z.

Figure A.2: Robustness Check of Model-Generate Bond Spread (1985Q1–2010Q4)



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 "event study" with rational learning. In our main exercise (purple line), estimate the learning parameters using an expanding window and feed them into the model period-by-period. 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.