Credit Cycles, Expectations, and Corporate Investment*

Huseyin Gulen
Purdue University

Mihai Ion
University of Arizona

Stefano Rossi
Bocconi University

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Abstract

We study the real effects of credit market sentiment on corporate investment and financing for a comprehensive panel of U.S. public and private firms over 1963-2016. In the short term, we find that high credit market sentiment in year t correlates with high corporate investment and debt issuance in year $t+1$, particularly for financially constrained firms. In the longer term, high credit market sentiment in year t correlates with a decline in debt issuance in years $t+3$ and $t+4$; and with a decline in corporate investment in years $t+4$ and $t+5$. This pattern of increased investment in the short term and declined investment in the longer term is more pronounced for firms with larger analysts' earnings forecast revisions and comes with larger analysts' forecast errors, supporting theories of over-extrapolation of fundamentals into the future. A parsimonious dynamic model where over-extrapolation is the only departure from standard Q-theory does a good job matching the empirical moments of our data.

Keywords: Credit-market sentiment, credit cycles, corporate investment, over-extrapolation

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1. Introduction

In aftermath of the credit boom of 2006-2007 and the subsequent financial crisis and Great Recession, recent empirical work documents a systematic connection between financial markets' cycles and the real economy. Credit expansions predict lower GDP growth (e.g., Schularick and Taylor 2012, López-Salido, Stein, and Zakrajšek 2017), lower returns in bank stocks (Baron and Xiong 2017), and lower returns in corporate bonds (Greenwood and Hanson 2013). One hypothesis, dating back to Minsky (1977), holds that these boom-bust patterns in credit and output growth reflect swings in non-rational expectations by economic agents. Good news about fundamentals make investors and managers too optimistic. In turn, excessive optimism drives an excessive decrease in the cost of capital, inducing managers to borrow and invest too much; subsequently, systematic disappointment triggers abrupt reversals in credit and investment. Bordalo, Gennaioli, and Shleifer (2018) propose a formal model of this mechanism under diagnostic expectations and present supportive empirical evidence that the expectations of credit analysts about future credit conditions are extrapolative. To assess the role of expectations, however, much remains to be done.

In this paper, we seek to provide a systematic empirical assessment of the Minsky hypothesis by investigating the connection between expectations, credit, and investment. First, we study the connection in the aggregate between analysts' expectations about future fundamentals of individual firms and credit cycles. Second, we assess the link between these credit cycles and these same expectations with firm-level borrowing and investment. Third, we assess whether analysts' disappointment, as measured by forecast revisions and forecast errors, occurs systematically in connection with reversals in credit conditions, borrowing, and investment. We perform this exercise systematically, using firm-level data and allowing for the estimated effects to differ between financially constrained and unconstrained firms. We also perform a calibration exercise in which we assess the ability of a standard Q-theory investment model augmented with diagnostic expectations to account for the key patterns in the data.

We begin by showing that credit cycles are tightly linked to systematic errors in analysts' expectations of future fundamentals. Specifically, we show that the credit market sentiment measure of Greenwood and Hanson (2013) strongly correlates positively with a measure of lagged analysts' consensus earnings forecast revisions and with measures of excess analyst optimism. The more analysts revise upward their expectations in year $t-1$, the more credit expands and credit quality deteriorates in year t. Consistent with the Minsky hypothesis, analysts' optimism drives down the cost of capital, and credit expands via a disproportionate issuance of junk bonds. Furthermore, we show that credit market booms in year t are followed by systematic downward revisions in analysts' consensus earnings forecasts, and these downward revisions are strongest in years $t+3$ and $t+4$. Thus, credit expansions are followed by systematic disappointment in expectations by analysts. As a result, aggregate cycles in expectations formation and revision explain a large proportion of the time series variation of the credit market sentiment measure of Greenwood and Hanson (2013). These findings point to systematic over-excitement by analysts, who over-extrapolate fundamentals into the future and then are systematically disappointed, again consistent with the Minsky hypothesis.

Armed with the evidence that credit market indicators are tightly connected with booms in optimism and systematic disappointment in expectations, we then examine firm-level responses to credit cycles using comprehensive panel data on the investment and financing of U.S. public and private firms over 1963-2016. Our objective is twofold. First, we wish to understand whether cycles in financial markets beget cycles in corporate investment and financing at the firm level. Second, to the extent that firm-level cycles in corporate investment and financing occur, we wish to examine whether financial analysts' expectations about firms' fundamentals play a role. To do so, we allow for heterogeneous effects of financial markets' cycles and analysts' expectations on financially constrained and unconstrained firms.

More specifically, we start with the aggregate measure of the quality of corporate debt issuers, developed by Greenwood and Hanson (2013), who show that the deterioration of issuer quality predicts low corporate bond excess returns. (See also Gilchrist and Zakrajšek 2012.) In principle, it is not obvious that credit market instability should affect corporate investment. When credit is cheap, firms could simply issue debt and repurchase shares; conversely, when credit is relatively expensive, firms could issue shares and reduce their outstanding debt. This way, firms would be acting as cross-market arbitrageurs (e.g., Ma 2018), thereby reducing instability in financial markets. As a result, financial market instability would just trigger a rebalancing of the firms' capital structure, with no effect on investment.

We begin by documenting that issuer quality drives firm-level corporate investment. We measure corporate investment using the methodology of Peters and Taylor (2017), which allows us to measure both investment in physical capital and in intangible capital. Our results are very strong for both types of investment. Overall, a one-standard-deviation increase in credit market sentiment is associated with a 5.1% increase in total investment the following year (relative to its mean), which represents the weighted average of a 6.8% increase in investment in physical capital and a 3.8% increase in investment in intangible capital.

Next, we examine the long-run effects of credit market sentiment on corporate investment and debt issuance by estimating impulse response functions using Jordá (2005)'s local projection method. We find significant reversals in that, following an increase in credit market sentiment in year t, corporate investment significantly declines in years $t+4$ and $t+5$; and both long-term debt issuance and short-term debt issuance significantly decline in years $t+3$ and $t+4$. Therefore, we find a one-year lag between the long-term effect of credit market sentiment on debt issuance, and its subsequent effect on corporate investment. We find little effect on equity issuance or on capital structure for the average firm. This is consistent with credit market sentiment affecting firms' balance sheets primarily by impacting investment in their tangible and intangible assets rather than by triggering capital structure rebalancing.[1]

We also examine the effects of credit market sentiment on syndicated lending. Syndicated lending represents a significant subset of the lending market, which has attracted much recent attention as a transmission mechanism of credit shocks to firm employment (see Chodorow-Reich 2014). We find muted short-term effects of high credit market sentiment in year t on syndicated lending in years $t+1$ to $t+3$, and we find negative, large, and strongly statistically significant effects of high credit market sentiment in year t on loan origination in years $t+4$ and $t+5$.

In sum, we document a novel real effect of credit cycles by showing that credit market shocks transmit to the balance sheet and capital investment programs of corporations. Credit market cycles beget corporate investment cycles. In the short term (one year after the credit market boom), firms' corporate investment increases. In the longer term, credit dries out (three and four years after the credit market boom) including short-term debt, long-term debt, and syndicated loan origination, which results in a strong contraction in corporate investment (four and five years after the credit market boom).

[1] We examine how these results depend on firm size, and we find that firms in the top size decile do rebalance their capital structure, consistent with the results of Ma (2018). However, even those firms in the top size decile experience both a significant short-term increase and a longer-term reduction in corporate investment.

To establish the mechanism driving our results and to evaluate the Minsky hypothesis in our data we turn to a systematic direct examination of data on expectations in the cross section of firms. Over-extrapolation implies that firms for which investors are more optimistic should exhibit both a larger short-term boom and a larger long-term reversal in both investment and financing (see Bordalo, Gennaioli, and Shleifer 2018). Consistent with this view, we find that after a credit market boom in year t, firms in the largest decile of analyst forecast revisions exhibit both larger increases in investment in year $t+1$ and larger declines in years $t+4$ and $t+5$ relative to firms in the bottom decile of analyst forecast revisions. We find similar results for total debt issuance. Finally, we find that firms with larger analyst forecast revisions exhibit larger negative forecast errors in the long run, particularly after a credit market shock.

We demonstrate that the strong effect of credit market sentiment on corporate investment is robust to controlling for a large set of aggregate proxies for first- and second-moment shocks to the economy. One advantage of our panel analysis is that unlike purely aggregate analyses, in addition to economy-wide indicators we can also directly control for a host of firm-level determinants of investment activity. This allows us to show that the strong effect of issuer quality on corporate investment is not due to time-invariant firm-level heterogeneity, time-varying firm-level default risk, or other firm-level proxies for investment opportunities and balance sheet strength.

To explicitly allow for firm heterogeneity, we first note that the financial frictions literature, as well as the model in Stein (1996), imply that buoyant credit market conditions will cause an increase in investment by financially constrained firms that need (bank or bond) debt to finance their marginal investment opportunities. Absent a credit boom, these debt-dependent firms would pass up projects with positive net present value (NPV). Accordingly, one would expect a credit market boom to increase investment, particularly of debt-dependent firms that are financially constrained.

We test several implications of this channel. We begin by relying on several existing metrics of financing constraints and dependence on external financing, drawing in particular on the work of Hadlock and Pierce (2010) and Whited and Wu (2006). These authors have developed indices of financial constraints that are by now standard in large-sample empirical work. We also employ an indicator variable for the absence of a credit rating, because Faulkender and Petersen (2006) argue that firms without a credit rating have no access to public bond markets.

One concern with these measures is that they might capture a generic dependence on external financing (both debt and equity) rather than exclusively a dependence on debt. To address this concern, we use two additional strategies to further rule out that our results are driven by a dependence on equity financing. The first relies on an indicator variable for privately listed firms. These firms are generally small and young, and, by definition, have no access to public equity markets, so to the extent they rely on external financing, it is external debt rather than equity. The second strategy is based on the framework in Stein (1996) and Baker, Stein, and Wurgler (2003) who posit that firms dependent on external debt financing are those firms whose marginal investment project is usually financed with a large fraction of external debt, namely, firms that at the same time depend on external financing and have unused debt capacity.[2]

Our results are very strong and consistent across all our proxies for debt dependence and financial constraints. We find strong support for the prediction that debt-dependent firms have the strongest correlation between issuer quality and subsequent investment, both tangible and intangible. In particular, while the effect of credit market sentiment on investment is strongly statistically significant for all firms, the magnitude of this effect is 50% to 100% larger among debt dependent firms.[3] At the same time, we find that in the long run the reversals in corporate investment and financing are strong across the board, and not significantly different in financially constrained or unconstrained firms. As a result, while financial frictions help explain the short-run response of investment and financing to credit shocks, financial frictions alone cannot solely explain boom-bust patterns in investment and credit.

Our results are consistent with a framework in which predictable cycles in credit markets beget predictable cycles in corporate investment activity, which occur through the revision of biased expectations and subsequent systematic expectation errors. There are two main possibilities. On the one hand, managers and investors may share the same biased beliefs about underlying fundamentals (see, e.g., Bordalo, Gennaioli, and Shleifer 2018). On the other hand, there may be disagreement among managers and investors, so that managers may think credit is mispriced (see, e.g., Stein 1996, Baker, Stein, and Wurgler 2003). Both views clearly have a strong empirical content in our context. For example, the view that managers and investors share the same biased beliefs explains

[2]While both Stein (1996) and Baker, Stein, and Wurgler (2003) focus explicitly on equity mispricing and equity-dependent firms, their argument can be similarly cast in terms of debt mispricing and debt-dependent firms.

[3]In unreported results, we also examine the possibility of an over-investment channel, according to which unconstrained firms take advantage of cheap credit to fund negative NPV projects. Using a number of empirical strategies to define firms potentially prone to over-investment, we find little or no support for this channel.

why corporate investment cycles are stronger for firms with larger forecast revisions and forecast errors; and the view that managers and investors disagree explains why the effect of credit market sentiment on corporate investment is stronger for debt dependent firms. While our data cannot conclusively distinguish these two interpretations, we document that a parsimonious dynamic model of investment where over-extrapolation is the only departure from standard Q-theory does a good job matching the empirical moments of our data.[4]

We contribute to the literature emphasizing cycles in credit markets and economic activity (López-Salido, Stein, and Zakrajšek 2017; Bordalo, Gennaioli, and Shleifer 2018) by emphasizing the role of expectations about fundamentals in generating and amplifying both financial markets cycles and cycles to firms' investment in tangible and intangible capital. Other papers have emphasized different mechanisms. Mian, Sufi, and Verner (2017) study household borrowing and do not examine expectations. Fahlenbrach, Prilmeier, and Stulz (2018) study intermediaries' balance sheets and, consistent with our findings, find that there is excess optimism for banks expanding credit more rapidly, but they do not examine credit spreads, firm-level investment or debt issuance. Real investment is a key element of business cycles, and the bond market is a key financing source for corporate investment in the U.S. Krishnamurthy and Muir (2017) show that changes in credit spreads and the extent of credit growth predict the severity of crises, suggesting expectations play a role but without examining data on expectations. Greenwood and Hanson (2015) study the dry bulk shipping industry and find that high current ship earnings are associated with high used ship prices and heightened industry investment in new ships, and forecast low future returns, but they do not examine data on expectations. Conversely, Gennaioli, Ma, and Shleifer (2016) examine data on expectations and corporate investment in the cross section, but they neither examine their dynamics over the cycle nor do they study how either expectations or investment vary with credit market sentiment. A different literature starting with Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) emphasize financial frictions as a transmission mechanism of productivity shocks to economic activity. These literatures help organize our analysis about the economic mechanisms at play in our data, and we discuss them in more detail in Section 6.

[4]These results are remarkable, because in our framework the cost of capital is constant, so that fluctuations in borrowing and investment are only due to expectations-driven changes in credit demand. The fluctuations would be larger if the model also took into account the mispricing of credit, in line with the evidence in Greenwood and Hanson (2013). More research is needed to assess the extent to which mispricing of credit is due to biased expectations of fundamentals such as default rates or to excessive extrapolation of past market conditions.

The paper proceeds as follows. Section 2 discusses data. Section 3 presents time series evidence of the connection between analysts' expectations and credit cycles. Section 4 documents the baseline effects of credit market sentiment on corporate investment and debt issuance in the short run. Section 5 presents the evidence on the long term effects of credit market sentiment on corporate investment and financing. Section 6 discusses the relevant theories of macroeconomics and finance and analyzes them within the context of the neoclassical Q-theory of investment, augmented with financial frictions and over-extrapolative expectations. Section 7 presents further empirical tests designed to explore the economic mechanisms. Section 8 concludes.

2. Data

This section describes our data and methodology. In sub-section 2.1 we describe firm-level data; in sub-section 2.2 we describe our measure of credit market sentiment; and in sub-section 2.3 we describe macro-level data.

2.1. Firm-level data

We study a large, unbalanced panel of Compustat firms at annual frequency that spans 1963 through 2016. The panel excludes financial firms (i.e., firms with a one-digit SIC code of six), utilities (i.e., firms with two-digit SIC code of 49), firms not incorporated in the U.S., and firm-years with negative assets, sales, or book equity. Otherwise, it includes all observations with data on investment, financing, debt dependence, and other investment determinants, as described below. All variables are winsorized at the 1^{st} and 99^{th} percentiles. Table 1 presents summary statistics of firm-level variables. We have over 120,000 firm-year observations and a median number of 2,503 firms in a given year.

2.2. Measuring credit-market sentiment

Throughout the paper we measure credit market sentiment using the index developed by Greenwood and Hanson (2013). This index is designed to capture the average issuer quality in the economy. Specifically, it is calculated as the difference between the average of default probabilities of firms with the highest net debt issuance in a given year, and the average of default probabilities of firms with the lowest net debt issuance that year. Default probabilities at the firm level are estimated as in Bharath and Shumway (2008), and can be thought of as statistically equivalent to a credit rating, with the added benefit that it can be computed for a large set of firms, starting in 1963. Net debt issuance is the change in total assets minus the change in book equity, with everything scaled by lagged total assets. Firms are categorized as high (low) net debt issuance if they are in the top (bottom) NYSE net debt issuance quintile.

Figure 1 plots this credit market sentiment index from 1963 to 2016, together with the NBER recessions (the shaded areas). Greenwood and Hanson (2013) show that this variable significantly negatively predicts excess corporate bond returns in the following two years. Therefore, when we refer to a credit market boom, or when we say that credit sentiment is high, we mean that the expected return to bearing credit risk is low, according to the forecasting model of Greenwood and Hanson (2013).

2.3. Macro-level data

Macroeconomic variables are measured at the end of the firm's current fiscal year. If macroeconomic variables are reported at a higher frequency than annual, we use an average of their values over the past year. Table 2 reports the correlations of our measure of credit market sentiment with a host of macroeconomic variables. It shows that credit market sentiment correlates positively with two measures of sentiment — the Michigan Consumer Confidence Index (p-value of 4%), and the Baker and Wurgler investor sentiment index (p-value of 7%). Credit market sentiment is uncorrelated with various macroeconomic proxies for investment opportunities, such as the Leading Economic Indicator from the Conference Board, the Chicago Fed National activity index, and the forecasted GDP growth from the Philadelphia FED Survey of Professional Forecasters. Credit market sentiment is also uncorrelated with various proxies of economic uncertainty, such as the Jurado, Ludvigson, and Ng (2015) index, the VXO index, and the GDP growth forecast disagreement index. Finally, credit market sentiment is uncorrelated with the default spread, the term spread, and Shiller's PE ratio.

3. Expectations and Credit Cycles

In this section, we examine the connection in the aggregate between measures of expectations and credit market sentiment. Ideally, we would like to use a direct measure of credit market expectations to assess empirically the Minsky hypothesis. Unfortunately, a sufficient time series data on credit market expectations is not available. One alternative is to use equity market expectations from survey data, as survey expectations about aggregate equity market returns are shown to be extrapolative. (See Greenwood and Shleifer (2014), Barberis, Greenwood, Jin, and Shleifer (2015, 2018), and Cassella and Gulen (2018)). One concern about the use of survey data on equity market expectations is that it is not obvious whether survey participants extrapolate past equity returns, market fundamentals such as past cash flows, or both. At the same time, to the extent that credit investors' expectations are tightly linked to underlying fundamentals, a measure of expectations of firm fundamentals can serve as a good proxy for the credit investors' expectations.

Therefore, we use analyst forecasts and forecast revisions from IBES to form a proxy for credit investors' expectations. We argue that this metric is highly correlated with expectations on company debt, and hence it provides a good proxy for investors' beliefs on firms' creditworthiness. Our use of analyst forecasts is also motivated by the findings of Greenwood and Shleifer (2014) who show that alternative measures of survey expectations about equity returns by different market participants (such as individual investors, professional investors, chief financial officers (CFOs), and U.S. consumers) are highly correlated. Similarly, we argue that, to the extent that a specific behavioral trait such as over-extrapolation of past outcomes is prevalent over a certain period, it is likely that both analysts forming expectations about future fundamentals and credit investors forming expectations about the creditworthiness of the same firm feature the similar behavioral trait. Furthermore, one significant advantage of using analyst data from IBES is that the IBES database covers a broad cross-section of firms over a long period of time, which allows us to conduct tests with sufficient statistical power.

Specifically, for each firm i and fiscal year t, each time an analyst consensus forecast is issued for the current fiscal year EPS, we calculate the difference between that forecast and the consensus forecast for the same figure made 12 months prior. We take an average of these forecast revisions during each fiscal year, and we normalize this average forecast revision by the stock price two days prior to the first forecast made in the previous year. In other words, we compute

$$\text{Revision}_{i,t+1} = \frac{\mathbb{E}_{i,t}\left[\mathbb{E}^{\theta}_{i,t+1}\left(\pi_{i,t+2}\right) - \mathbb{E}^{\theta}_{i,t}\left(\pi_{i,t+2}\right)\right]}{P_{i,t}}$$

so as to ensure that $\mathbb{E}_{i,t}\left[\text{Revision}_{i,t+1}\right] = 0$.[5]

In Figure 2, we plot cross-sectional averages of the above forecast revision variable alongside the credit market sentiment index. A visual inspection of the figure suggests that analyst forecast revisions, on average, tend to lead the credit market sentiment index. Indeed, when we regress the credit market sentiment index on lagged average analyst forecast revisions and the macroeconomic controls used in our main tests, we obtain a coefficient of 0.32 with a t-statistic of 1.98 (p-value of 5.6%). Therefore, upward revisions of analysts' forecasts predict a credit expansion together with a deterioration of credit quality, which occurs through the disproportionate issuance of speculative-grade "junk" bonds.

To delve deeper and examine whether the credit market sentiment index reflects the revision of biased expectations, we compute a measure of "excess analyst optimism" as the average analyst EPS forecast of issuers of speculative-grade bonds minus the average analyst forecast of investment-grade bond issuers. To determine credit risk, we use Standard and Poor's credit ratings from Compustat. Each year, we split firms into investment-grade issuers (credit rating of BBB or higher) and speculative-grade issuers (credit rating lower than BBB). Figure 3 plots this measure of excess analyst optimism against the credit market sentiment index and shows that the two series are strongly positively correlated. The correlation between the two series is 32%. Therefore, in times of high credit market sentiment, analysts are disproportionately more optimistic about speculative-grade bond issuers relative to investment grade bond issuers, which is again consistent with over-extrapolation.

Collectively, these results indicate that the more analysts revise upward their expectations in year $t-1$, the more credit expands and credit quality deteriorates in year t, indicating that credit market sentiment reflects an excessive extrapolation of past market conditions. Consistent with the Minsky hypothesis, increases in analysts' optimism drive down the cost of capital, and as a result

[5] Following Clement and Tse (2005), each fiscal year, we use all the forecast revisions occurring no later than 30 days prior to the fiscal year end.

credit expands via a disproportionate issuance of junk bonds.

Of course, over-extrapolation also implies that following a credit market boom, analysts become systematically disappointed and revise their forecasts downward. To investigate this prediction, we compute future EPS forecast revisions as the difference between consensus forecasts made at the beginning of calendar year $t+k$ about the level of EPS in year $t+k$ (one-year ahead forecast), and the consensus forecasts made at the beginning of calendar year $t+k-1$ about the level of EPS in year $t+k$ (two-year ahead forecast). We find a negative correlation between this EPS forecast revision variable and credit market sentiment. The correlation coefficient is statistically significant for $k=2$, $k=3$, and $k=4$, and it increases in magnitude with k. Figure 4 reports the correlation for $k=4$. As a result, credit market sentiment in the aggregate appears to be tightly linked to biased analyst expectations and their subsequent forecast revisions.

We conclude that credit expansions are followed by systematic disappointment in expectations by analysts. As a result, aggregate cycles in expectations formation and revision explain a large proportion of the time series variation of the credit market sentiment measure of Greenwood and Hanson (2013). Collectively, our results indicate that cycles in expectations and in credit markets go hand in hand, providing strong support to the Minsky hypothesis. Analysts become systematically over-excited about future fundamentals, which predicts credit expansion through the disproportionate issuance of junk bonds. In turn, credit expansion predicts a systematic disappointment by the same analysts, who as a result revise their expectations downward, predicting in turn a credit reversal.

Having established that in the aggregate credit market sentiment is tightly connected with booms in optimism and systematic disappointment in expectations, in the next section we examine the responses of firm-level investment and financing to aggregate credit cycles using comprehensive panel data on U.S. public and private firms over 1963-2016.

4. Credit Cycles and Corporate Investment

In this section, we present our results on credit and investment. In sub-section 4.1 we describe our approach. In sub-section 4.2 we present the results from our baseline specifications; in sub-section 4.3 we examine a debt financing channel.

4.1. Baseline specification

Our baseline regressions will generally take the following form:

$$Y_{i,t+k} = \alpha_i + \beta_k CMS_t + \gamma F_{i,t} + \delta M_t + \varepsilon_{i,t+k} \tag{1}$$

where $Y_{i,t+k}$ are going to be measures of corporate investment in tangible capital, intangibles, and both, and measures of financing including short-term debt, long-term debt, total debt issuance, syndicated loan origination, and syndicated loan refinancing. CMS_t is the credit market sentiment index described above, $F_{i,t}$ is a vector of firm-level controls, M_t is a vector of macro-level controls, and α_i is a set of firm fixed effects. We will discuss these controls in more detail when we report our results. k indexes the year in which the dependent variable is measured relative to year t in which the independent variables are measured. Consequently, $k = 1$ indexes the year after the independent variables are measured, while $k = 5$ indexes 5 years after.

Estimating equation (1) for increasing values of k traces out the Jordá (2005) local projection impulse response function β_k. In the first part of the paper, we will take $k = 1$ as in standard investment regressions. In the second part of the paper, we will examine longer-term effects at $k = 2, 3, 4, 5$. Standard errors are computed using the Driscoll and Kraay (1998) method to account for time series correlation between error terms.[6]

4.2. Baseline results

We begin by reporting in Table 3 the results from estimating equation 1 for $k = 1$, using as dependent variables firm-level total investment, investment in physical assets, and investment in intangible assets. To build these measures, we follow Peters and Taylor (2017), who show that intangible capital has become an increasingly important factor of production and should therefore be included in any analysis of corporate investment activity. Specifically, total capital is gross PPE (i.e., physical capital) plus the sum of goodwill, capitalized R&D, and capitalized SG&A (i.e., intangible capital). Total investment is the percentage change in total capital, investment in physical capital is the change in physical capital divided by lagged total capital, and investment in intangible capital is the change in intangible capital divided by lagged total capital. Tobin's Q is

[6] In a previous draft we clustered standard errors at the firm and year level, and our results were very similar.

the market value of equity plus book value of debt divided by total capital.

The first three columns in Table 3 show that higher credit market sentiment in year t is associated with an increase in total corporate investment in year $t+1$.[7] This result is statistically significant at the 1% level. It holds true in the baseline test of column 1 that controls for Tobin's Q and the ratio of cash flow to assets, and in column 2 where we add as additional covariates several controls for the strength of the balance sheet, namely, the log of total assets to proxy for firm size, the ratio of cash to assets and the ratio of book leverage to proxy for corporate liquidity, and sales growth and ROA to proxy for the firm's operating performance. The estimated coefficients on the covariates have the expected sign, in that firms with higher investment opportunities, higher liquidity, and better performance invest more. None of the covariates affects our baseline result. In column 3, we add controls for potentially confounding macroeconomic conditions to our baseline specification. We control for (i) aggregate investment opportunities (Leading Economic Indicator Index from the Conference Board), (ii) macroeconomic uncertainty (the Jurado, Ludvigson, and Ng (2015) index), (iii) mispricing in equity markets (the Baker and Wurgler (2006) sentiment index), and (iv) the aggregate valuation of debt (the default spread).

Furthermore, we address the possibility that the effect of credit market sentiment on corporate investment that we have documented operates through firm-level credit risk. There are two possibilities. First, if a boom in credit market sentiment increases credit risk at the firm level, then we should observe an increase in both firm-level default probability and firm-level investment through an asset-substitution-type of mechanism, as argued for example by Gomes, Grotteria, and Wachter (2018). Alternatively, higher credit risk may come with poor investment opportunities, giving rise to lower subsequent investment. To examine these possibilities, in column 3 of Table 3 we add not only the macroeconomic variables described above but also a proxy for firm-level default probability, such as the Bharath and Shumway (2008) index.[8] Higher firm-level default probability is negatively associated with subsequent investment. Our results are unaffected, and their economic magnitude, if anything, is larger than in column 2. In economic terms, in our strictest specification

[7] To facilitate the interpretation of the economic magnitudes, all left-hand-side variables are divided by their sample mean and all right-hand-side variables are demeaned and divided by their sample standard deviation. As a result, all estimated coefficients can be interpreted as the percentage change—relative to the mean—in the left-hand-side variable associated with a one standard deviation increase—relative to the mean—in the right-hand-side variable.

[8] We show in Table D.1 in the Appendix that we obtain similar results under alternative proxies of credit quality such as the Campbell, Hilscher, and Szilagyi (2008) index, the Ohlson (1980) O index, and the Altman (1968) Z score.

(column 3), a one standard deviation increase in credit market sentiment relative to its mean is associated with a 5.1% increase in corporate investment relative to its mean.

As noted in the previous section, our measure of corporate investment considers expenditures in both tangible and intangible capital. Therefore, in columns 4 to 6 we repeat our baseline tests by studying investment in tangible assets as a dependent variable; and in columns 7 to 9 we study investment in intangible assets as a dependent variable. Our results are strongly statistically significant throughout for both measures of corporate investment. In economic terms, a one standard deviation increase in credit market sentiment is associated with a 6.8% increase in investment in tangible capital (column 6), and a 3.8% increase in investment in intangible capital (column 9). In what follows, we take as starting point the specifications of column 3 (and columns 6 and 9) of Table 3, and we will refer to it as our baseline specification.

In sum, our evidence shows that a credit market boom in year t comes with increased corporate investment in year $t+1$, be it investment in tangible capital, intangible capital, or both. In the next section, we explore a specific debt-financing channel.

4.3. Debt financing channel

So far, we have established a correlation of credit market sentiment with subsequent corporate investment in a large sample of U.S. publicly listed firms. In this section, we allow for firm heterogeneity and examine the predictions of the financial frictions literature (e.g., Bernanke and Gertler (1989), Kiyotaki and Moore (1997)) and of the behavioral literature (e.g., Stein (1996) and Baker, Stein, and Wurgler (2003)). While based on different mechanisms, these literatures share the cross-sectional prediction that the effects of credit market sentiment on corporate investment should be more pronounced for firms more dependent on external financing.

Specifically, we use two empirical strategies for isolating a debt financing channel. First, we examine the hypothesis from the financial frictions literature that the marginal effect of credit market sentiment should be larger for more financially constrained firms. We use three proxies for financial constraints, namely, the indices of financial constraints developed by Hadlock and Pierce (2010) and by Whited and Wu (2006), which have become prevalent in more recent literature.[9]

[9]See, for example, Chava and Roberts (2008), Van Binsbergen, Graham, and Yang (2010), Li (2011), Hann, Ogneva, and Ozbas (2013), Leary and Roberts (2014), Erel, Jang, and Weisbach (2015), and Almeida, Fos, and Kronlund (2016).

In addition, we note, following Faulkender and Petersen (2006), that firms without a credit rating have no access to public bond markets, and are also in general smaller and younger, and as such are likely to have a higher cost of external financing. So, we construct an additional indicator variable equal to one for firms that never had a credit rating but currently have positive debt outstanding.

Table 4 presents our results. We use total corporate investment as the dependent variable in Panel A and net debt issuance in Panel B. In both panels, we report results using all three proxies for financial constraints: the Hadlock and Pierce (2010) index in columns 1 to 3, the Whited and Wu (2006) index in columns 4 to 6, and the credit rating indicator in columns 7 to 9. We refer to financially constrained firms as firms without a credit rating, and as firms in the top tercile of either the Hadlock and Pierce (2010) or the Whited and Wu (2006) indices. We report both results using an interaction between credit market sentiment and each proxy (columns 3, 6 and 9), as well as results in separate subsamples based on splitting the sample with respect to each proxy (the remaining columns).

Panel A shows that throughout all three proxies for financial constraints, firms that are more financially constrained display a larger sensitivity of investment with respect to credit market sentiment. Panel B shows that firms that are more financially constrained display a larger sensitivity of total net debt issuance with respect to credit market sentiment. Under standard pecking order theory (e.g., Myers (1984)), financially constrained firms depend on external financing, and such dependence also coincides with a dependence on external debt financing. Consequently, our results in Table 4 can be interpreted as consistent with the financial frictions literature.

Our second strategy to isolate a debt financing channel explicitly considers the theories of Stein (1996) and Baker, Stein, and Wurgler (2003). So far, one challenge in interpreting our results in Table 4 along the lines of Stein (1996) and Baker, Stein, and Wurgler (2003) is that these firms, by being publicly listed, also have access to public equity markets. So, in principle there is a confounding effect in that our results might also reflect a generic dependence on equity markets and thus equity market sentiment. We do control for equity market sentiment in various ways (for example, using Tobin's Q and the Baker and Wurgler equity market sentiment index), but to the extent that such controls are imperfect, concerns may arise that our results capture a general capital market mispricing rather than a more precise debt-financing channel. In this section, we attempt to sharpen the interpretation of our results by isolating a subset of firms for which the confounding effect of equity market sentiment is further mitigated or even eliminated by using several alternative strategies. None of these strategies is likely to be perfect in itself, but to the extent that they provide consistent results they will greatly increase our confidence that we have isolated a debt financing channel.

In the framework of Stein (1996) and Baker, Stein, and Wurgler (2003) managers and investors disagree about debt mispricing, so managers issue debt to finance their marginal investment opportunity if they believe debt is cheap.[10] Accordingly, we develop two additional debt dependence proxies. The first is a straightforward application of the idea in Stein (1996) that debt dependent firms have *both* high financial constraints and unused debt capacity. Therefore, we construct this proxy for debt dependence by interacting the Hadlock and Pierce HP index of financial constraints defined above with the measure of target leverage developed by Faulkender, Flannery, Hankins, and Smith (2012). Specifically, we construct our proxy of debt dependence as an indicator that equals one if the firm-year observation is *both* above the median in the Hadlock and Pierce index *and* above the median in target leverage.[11] We denote these firms DD(HP).

The second proxy follows similar logic, but it is based on textual analysis of 10-K filings following the work of Hoberg and Maksimovic (2015, henceforth HM), whereby a firm is defined as constrained if its 10-Ks suggest that the firm is at risk of delaying investment due to issues of liquidity. HM also checks if firms suggest that they will most likely have to issue debt to address this concern (HM calls this the "debtdelaycon" measure), or if they are likely to have to issue equity (HM calls this the "equitydelaycon" measure). Using the HM metrics, we define a firm-year as debt dependent if in that year the firm is both likely to have to issue debt to address liquidity needs (i.e., above median in the "debtdelaycon" measure) and unlikely to need to issue equity for liquidity purposes (i.e., below median in the "equitydelaycon" measure). We denote these firms DD(HM).

We complement these strategies by examining a sample of private firms obtained from Capital IQ.[12] Private firms tend to be smaller and younger than their public counterparts and, by definition,

[10]While both Stein (1996) and Baker, Stein, and Wurgler (2003) focus explicitly on equity mispricing and equity-dependent firms, their argument can be similarly cast in terms of debt mispricing and debt-dependent firms.

[11]We obtain similar results if we interact target leverage with the Whited and Wu (2006) index.

[12]Capital IQ provides data on firms that file Form 10-K or Form S-1. According to the SEC, firms must file Form 10-K if they have 500 or more shareholders and total assets of at least $10 million. In addition, firms with public debt must file Form S-1. Therefore, compared to the universe of private firms, private firms in our sample are relatively large, and either have already issued public debt or plan to do so. Capital IQ's private firm data is described in more detail in Gao, Harford, and Li (2013), Phillips and Sertsios (2016), and Acharya and Xu (2017).

have no access to external public equity markets. Therefore, it is plausible that private firms finance their marginal investment opportunities with a mixture of internal funds and external (bank or bond) debt. The advantage of this strategy is that, to the extent that we can document an association between credit market sentiment and investment for these private firms, we can be confident that the channel is a debt-financing one. On the other hand, data on the balance sheet of private firms is more limited, so we cannot control for the same extensive set of firm characteristics as in our previous tests.

Table 5 presents the results. The dependent variable in Panel A is total corporate investment (as defined in Peters and Taylor (2017)). In Panel B, it is total net debt issuance (change in total assets minus change in book equity, with everything divided by lagged total assets). Our proxy for debt dependence is the firm's public/private status in the first three columns of each panel, and the DD(HP) and DD(HM) indicators defined above in the other columns. We present specifications using interactions of credit market sentiment with debt dependence (columns 3, 6, and 9), as well as specifications run on separate samples of firms split on debt dependence (the remaining columns.)

The first three columns in Panel A show that the effect of credit market sentiment on corporate investment is larger for private firms than for public firms, although it is positive and strongly significant for both. In economic terms, column 2 suggests that a one standard deviation increase in credit market sentiment is associated with a 11.8% increase in investment, relative to the mean, for private firms. This effect is 2.4 times larger than for public firms (column 1). The other columns in Panel A show that among public firms, the effect of credit market sentiment on investment is larger for firms with large debt dependence, be it measured by the DD(HP) or the DD(HM) indicator. Overall, the results are consistent with credit market sentiment affecting corporate investment through a debt-dependence channel.

5. Long-Term Effects

In this section, we examine long term effects. In sub-section 5.1, we examine long-term effects of credit market sentiment on investment and financing, and in sub-section 5.2 we examine cross-sectional heterogeneity in these long-term effects.

5.1. Long-term effects of credit market sentiment on corporate investment and financing

In this section, we explore the longer term effects of credit market sentiment. There is evidence of strong reversals in aggregate economic activity following credit booms (see López-Salido, Stein, and Zakrajšek 2017). Baron and Xiong (2017) show that credit booms are followed by stock market declines. They document that banks expand their loans in good times, and this expansion predicts future negative returns on bank equity. In a related vein, Jordá, Schularick, and Taylor (2013) show that strong growth of bank loans forecasts future financial crises and output drops (see also Fahlenbrach, Prilmeier, and Stulz (2018)). In this section, we examine whether credit market sentiment also affects corporate investment and debt financing for several years following a credit market shock.

We begin by examining corporate investment. We estimate versions of equation (1) with k taking values from 1 to 5 (years) to trace out the Jordá (2005) local projection impulse response function β_k.[13] We hold constant our controls of the baseline specification of column 3 of Table 3.

Table 6 presents the results. For comparison purposes, the first column reports the one-year ahead effect of credit market sentiment from column 3 of Table 3. Columns 2 to 5 examine the longer term effects, from year $t+2$ to year $t+5$, of credit market sentiment shock in year t. The effect in year $t+2$ is still positive, although insignificant. Then, from year $t+3$, the effect turns negative and becomes statistically significant at the 1% level in years $t+4$ and $t+5$. Importantly, the economic magnitude of these long-term reversals is larger than its short-term counterpart. In fact, a one standard deviation increase in credit market sentiment in year t comes with a 5.1% increase in investment in year $t+1$, with a 5.6% decrease in investment in year $t+4$, and with a 5.4% decrease in investment in year $t+5$.

Panel B of Table 6 examines investment in physical capital, and Panel C of Table 6 examines investment in intangible capital. Both investment in physical and intangible capital respond to credit market sentiment with the same pattern of boom in year $t+1$ and reversal in $t+4$ and $t+5$. Interestingly, the economic magnitude of the investment boom in year $t+1$ is about 50% larger for investment in physical capital, but the economic magnitude of the reversals in years $t+4$ and

[13] A more general formulation of Jordá's (2005) local projection impulse response function includes a history of p lags of dependent and independent variables (e.g., Jordá, Schularick, and Taylor (2013) study a panel of 14 countries over 140 years and use $p=1$.) We also estimate versions of our equation (1) with $p=1$ and $p=2$, with and without firm fixed effects, and our results are unaffected.

$t + 5$ is larger for investment in intangible capital. This result points to a significant heterogeneity in the responsiveness of investment to credit market sentiment, and suggests that the longer-term reversals may be particularly costly for those firms and sectors of the economy that rely the most on investment in intangible assets, such as R&D.

Next, we examine the effects of credit market sentiment on the external financing of firms. Specifically, we want to determine which specific financing channel is associated with the documented patterns on corporate investment. Table 7 examines the effects of credit market sentiment on total net debt issuance (Panel A), longer-term net debt issuance (Panel B), and short-term net debt issuance (Panel C). The results show that a credit market sentiment boom in year t comes with an increase in total net debt issuance in year $t + 1$ (Panel A column 1). Interestingly, this result is entirely due to issuance of long-term net debt (Panel B column 1) rather than short-term net debt (Panel C column 1).

Longer-term debt issuance also exhibits a reversal. In fact, a credit market sentiment boom in year t accompanies a decrease in total net debt issuance in years $t+3$ and $t+4$ (Panel A, columns 3 and 4). Such reversal occurs both in long-term net debt (Panel B, columns 3 and 4) and short-term net debt issuance (Panel C, columns 3 and 4). The decline in long-term net debt issuance also continues in year $t + 5$ (Panel B, column 5).

In terms of economic magnitudes, a one standard deviation increase in credit market sentiment in year t accompanies an 11% increase in total net debt issuance in year $t + 1$ (respectively 22% increase in long-term debt issuance), with a 12%-13% decrease in total net debt issuance in both year $t+3$ and $t+4$. The magnitude of the reversal is larger in short-term debt issuance in year $t+3$ relative to long-term net debt issuance (14.4% decline versus 9% decline); in year $t + 4$ and $t + 5$ the decline is larger in long-term debt issuance (14% and 10.6% decline, respectively) relative to the decline in short-term net debt issuance (11% decline in year $t+4$ and no decline subsequently).

In Table 8, we examine the effects of credit market sentiment on syndicated lending. Syndicated lending represents a segment of the lending market that has recently received attention during the financial crisis as a transmission mechanism of credit shocks to firm employment (Chodorow-Reich 2014). We merge Dealscan data on syndicated lending with Compustat data using the concordance first developed in Chava and Roberts (2008) and updated on Michael Roberts' website.[14] Our final

[14] http://finance.wharton.upenn.edu/ mrrobert/styled-9/styled-12/index.html

sample contains 66,455 firm-year observations. Panel A examines all syndicated loans, including origination or refinancing, Panel B studies syndicated loan origination, and Panel C studies loan refinancing. Interestingly, a one standard deviation increase in credit market sentiment in year t is not associated with significant changes in either syndicated loan origination or refinancing in year $t+1$, $t+2$, or $t+3$. In years $t+4$ and $t+5$ however, syndicated loan origination declines by 16.5% and 13.2%, respectively, which translates into a 14% decline in total syndicated loans in year $t+4$. Overall, we find that while syndicated lending does not react to credit shocks in the following year $t+1$, even syndicated lending origination exhibits strong reversals in years $t+4$ and $t+5$. This reinforces the conclusion that long term reversals occur across the board for a wide array of firms and debt contracts.

We also explore the idea that a portion of the proceeds raised by issuing debt in response to credit market sentiment might be used to repurchase shares (Ma 2018). Tables D.2, D.3, and D.4 in the Appendix examine the effect of credit market sentiment on net debt issuance, net equity repurchases, and total external financing (net debt issuance minus net equity repurchases). We report results using all firms in our sample (Table D.2), only firms in the top size decile (Table D.3) and only firms in the bottom nine size deciles (Table D.4). These tables show that credit market sentiment is indeed associated with higher repurchases in year $t+1$ (Panel B in each table), but these higher repurchases are significantly lower than the corresponding increase in debt issuance in all but the largest 10% of firms (compare Panel C in Table D.3 with Panel C in Table D.4). In addition, for firms in the bottom nine size deciles, higher credit market sentiment in year t is associated with significantly lower net external financing in years $t+3$ to $t+5$. Finally, in Appendix Table D.5, we examine the long-term effects of credit market sentiment on corporate investment separately for firms in the top size decile (Panel B) and firms in the bottom nine size deciles (Panel C), and we find significant investment reversals in years $t+4$ and $t+5$ in both groups. To conclude, we find some evidence that firms act as cross-market arbitrageurs. That is, when credit is cheap firms issue debt and repurchase shares, consistent with Ma (2018). Yet, this evidence is confined to firms in the top size decile in our data. Even for those firms in the top size decile, we do find long term reversals in corporate investment following a credit market shock.

5.2. Heterogeneity in long-term effects

In this section, we examine heterogeneity in the reversal of real effects of credit market sentiment on investment and financing decisions of firms. We begin by performing our analysis separately on the 10 different sectors of the economy, as classified by Fama and French (1997).[15] Table D.6 in the Appendix shows that the positive effects of a credit market shock in year t on investment in year $t+1$ occurs in 8 out of 10 sectors. (Exceptions are the oil, gas, and coal sector, and the healthcare, medical equipment, and drugs sector.) Conversely, the reversals in investment in years $t+4$ and $t+5$ following a credit boom in year t occur in all sectors but non-durables (food, tobacco, etc.). Interestingly, the consumer durables and the wholesale retail sectors lead the way, in that for these sectors, the reversal begins already in year $t+3$. Table D.7 in the Appendix presents similar results for total net debt issuance.

Next, we continue to estimate equation 1 for k going from 1 to 5, and this time we condition separately on our proxies for debt dependence and financial constraints. For brevity, in Tables 9 and 10 we present the results using our DD(HP) measure of debt dependence (i.e. above median Hadlock and Pierce (2010) index and above median target leverage), but we verify that our results are qualitatively unchanged if we use any other measure of debt dependence of external financing constraints. Table 9 reports results on corporate investment, and Table 10 reports results on total net debt issuance. Panels A in both tables present results on the sub-sample of debt dependent firms, and Panels B present results for firms that are not debt dependent. In Panels C, we include the entire sample of firms and add an interaction between CMS and a debt dependence indicator to assess if the two groups of firms show differential responses to CMS shocks. Overall, Tables 9 and 10 show that the reversals in investment and in total net debt issuance documented above occur across the board, irrespective of debt dependence status. These reversals are large in economic terms and strongly statistically significant both for firms with high financial constraints and for firms with low financial constraints. Panels C show that, while debt dependent firms experience a significantly higher investment and debt issuance in year $t+1$ in response to an increase in CMS at time t, in the long run, the reversals are large for both debt dependent and non-debt-dependent firms and not significantly different between the two sub-samples.

[15] Fama and French (1997) originally classify firms in 12 sectors. We exclude utilities and financials, which is consistent with the rest of our analysis.

6. Theories of Credit Cycles and Investment

Our results highlight a robust positive correlation between high credit market sentiment in year t and corporate investment in both tangible and intangible capital in year $t+1$. This positive correlation is significantly stronger for debt-dependent, financially constrained firms. In the longer term, the effect reverses: high credit market sentiment in year t is followed by a large and significant reduction in corporate debt financing in years $t+3$ and $t+4$, and by a significant reduction in corporate investment in years $t+4$ and $t+5$. Interestingly, reversals are strong across the board, and not just limited to specific subsets of firms or industries. Figure 5 summarizes visually our empirical results. In this section, we discuss the theories that are most directly consistent with these results. We place existing theories in two broad groups: those relying on the revision of (rational) expectations and some kind of financial friction, and those relying on the revision of (biased) expectations alone. In the spirit of our integrated empirical setting, we immediately note that it is unlikely that either set of theories uniquely explains our results, and in general, both financial frictions and biased expectations are likely to matter in the data. However, a discussion of theory can shed light into the relative importance of different mechanisms in the data, and help design further tests to sharpen our understanding of the relevant theories. Sub-section 6.1 discusses theories of rational expectations and financial frictions; sub-section 6.2 discusses behavioral theories based on biased expectations; and sub-section 6.3 formalizes the preceding discussions in the context of the neoclassical Q-theory framework.

6.1. Rational expectations and financial frictions

The large literature on the macroeconomic role of financial frictions recognizes that exogenous shocks to prices or productivity, despite causing an immediate revision of expectations, may not generate an immediate adjustment of corporate borrowing and investment behavior in the presence of financial frictions.[16] The seminal contributions of Bernanke and Gertler (1989), Kiyotaki and Moore (1997), and Bernanke, Gertler, and Gilchrist (1999) highlight three main channels through which financial frictions affect the macroeconomy. First, when agents are levered, temporary shocks can have persistent effects on economic activity because they affect the agents' net worth, which

[16] In a different but related vein, Kydland and Prescott (1982) consider the presence of lags between investment plans and their realization, which alone can generate fluctuations in investment around a growth path.

takes time to rebuild. Second, shocks are directly amplified in the presence of leverage. Bernanke and Gertler (1989) and Carlstrom and Fuerst (1997) quantify of these effects by building on the idea that collateral value is costly to verify when information is asymmetric. Third, Kiyotaki and Moore (1997) show that shocks are further indirectly amplified through intertemporal feedback loops. In Kiyotaki and Moore (1997), an increase (re. decrease) in prices generates an increase (re. decrease) in the net worth of levered agents, thereby relaxing (re. tightening) their collateral constraints. This leads to an increase (re. decrease) in investment and output, which further increases (re. decreases) these agents' net worth.[17] Together, these insights show that even relatively small shocks can have potentially large effects on the macroeconomy.[18]

In these models, collateral constraints depend on asset values and are always binding, based on the idea that financial frictions generally prevent agents from investing up to the first best level. As a result, positive shocks to prices and collateral help agents invest closer to the first best. Furthermore, these models provide a justification for ex post policy interventions because after a positive shock, agents fail to internalize that their decision to borrow and invest will affect prices and future transmissions of the shocks.[19]

Kocherlakota (2000) argues that the quantitative degree of amplification of these models is sensitive to the model parameterization and is ultimately insufficient to explain observed fluctuations. Therefore, after the financial crisis of 2008-2009 more recent macroeconomic models of financial frictions focus on providing non-linear dynamics. Brunnermeier and Sannikov (2014) present a model in which constraints are binding only occasionally, so that at the steady state, firms absorb moderate shocks easily by adjusting payouts. However, after an unusually large shock, firms can no longer adjust payouts and need to deleverage, i.e., sell capital to cut down their exposures.[20] Similarly, Bianchi (2011) and Mendoza (2010) study international macro-finance models based on occasionally binding collateral constraints and externalities of individual borrowing decisions on

[17] This mechanism builds on the fire sales mechanism of Shleifer and Vishny (1992), according to which when a firm in financial distress needs to liquidate assets, the natural purchasers—firms in the same industry—are likely financially distressed, too. As a result, demand for liquidated assets will be low and the assets will trade at a fire-sale discount relative to their fundamental value.

[18] Khan and Thomas (2008, 2013) and Ottonello and Winberry (2018) explore these dynamics in models with heterogeneous firms.

[19] Scheinkman and Weiss (1986) and Cooley, Marimon, and Quadrini (2004) present related models in which borrowing constraints stem from enforcement frictions.

[20] He and Krishnamurthy (2012) study a related model in which the aggregate capital of the intermediary sector represents a key state variable for determining macroeconomic and asset pricing patterns during the financial crisis.

prices. These models also generate strong state dependency: Once the economy is in a crisis regime, even small shocks are subject to amplification, leading to significant endogenous risk.[21]

In our setting, these models explain why a credit market sentiment shock in year t should be followed by increased corporate borrowing and investment in year $t + 1$. They also explain why this effect should be stronger for debt-dependent firms, as we document in Table 4. These models have difficulty in rationalizing in a parsimonious way why aggregate shocks at time t do not just eventually die out, but instead generate a large and predictable reversal in corporate borrowing and investment in years $t+3$, $t+4$, and $t+5$ across the board for all types of firms and irrespective of financial frictions. To be sure, these reversals could reflect subsequent exogenous shocks of the opposite sign, or could be due mechanically to a strong negative moving average component in credit market sentiment. Yet, these explanations pose two problems. First, they are not parsimonious, as they posit that the time series structure of exogenous shocks closely mirrors the data patterns to be explained without specifying further falsifiable predictions. Second, these explanations neglect the fact that prior evidence shows a systematic, cyclical component in credit market sentiment, since a credit market sentiment boom in year t predicts *both* low returns in year $t + 1$ (Greenwood and Hanson 2013) *and* low aggregate economic activity in years $t + 3$ and $t + 4$ (López-Salido, Stein, and Zakrajšek 2017).

In fact, to the extent that these models can generate some longer term reversal in borrowing and investment, a common feature of the models in this literature is that the same financial friction that generates the short term amplification should also generate the longer term reversal, as we illustrate in Section 6.3 below. This prediction is at odds with our findings in Tables 9 and 10, where we find significant reversals across the board, both in high financial constraints and low financial constraints firms.

6.2. Biased expectations

A literature starting with Minsky (1977) and Kindleberger (1978) has stressed the role of biased expectations in generating and amplifying financial market cycles and economic fluctuations. More

[21] New Keynesian analyses emphasize a distinct but related mechanism that involves deleveraging and aggregate demand externalities. For example, Schmitt-Grohé and Uribe (2017) present a model in which, in the presence of downward nominal wage rigidity, a Taylor-type interest rate feedback rule, and a zero lower bound on nominal interest rates, a confidence shock can generate a slump in investment (see also Korinek and Simsek 2016 and Eggertsson and Krugman 2012).

recently, a set of theories emphasizes that credit market sentiment can affect investment exclusively through revisions of biased expectations. Greenwood and Hanson (2013) show that credit booms come with a deterioration of the credit quality of the average issuer of debt, and in the aggregate predict low subsequent returns to corporate bondholders. López-Salido, Stein, and Zakrajšek (2017) show that credit booms drive the aggregate mix of external financing and, in turn, subsequent aggregate fluctuations in economic activity. This approach emphasizes that, rather than a sequence of idiosyncratic unexpected shocks of opposite signs, financial market instability features cyclical and predictable components. Furthermore, it is difficult to reconcile these cyclical components with rational expectations. Under rational expectations one would expect that a credit boom with low average quality of debt issuance should be followed by higher subsequent credit risk and higher expected returns, which is the opposite of what the data show.

Accordingly, a small but growing number of recent studies present formal analyses of how behavioral biases affect economic activity. Bordalo, Gennaioli, and Shleifer (2018) present a model of diagnostic expectations whereby agents overweight future outcomes that become more likely in light of current data (see also Greenwood, Hanson, and Jin 2016). Greenwood and Hanson (2015) study investment boom-and-bust cycles and returns on capital in the dry bulk shipping industry and find that high current ship earnings are associated with high used ship prices and heightened industry investment in new ships, but forecast low future returns. In their model, firms over-extrapolate exogenous demand shocks and partially neglect the endogenous investment response of their competitors.

In these models, agents over-extrapolate a shock to fundamentals too far in the future. After a number of subsequent realizations turn out worse than expected, agents abruptly revise their expectations downward, generating a reversal. In these models, a single shock to fundamentals generates both positive short-term boosts and longer-term reversals in economic activity. In our setting, these models explain why shocks to fundamentals should propagate through credit supply via biased expectations, so that when fundamentals turn out worse than expected, firms redesign their investment plans, triggering long-term reversals in investment. In the next section, we formalize these ideas in a Q-theory framework. We then explore the over-extrapolation mechanism in more detail.

6.3. A Q-theory framework for investment cycles

In this section, we summarize the previous discussion within the context of the neoclassical Q-theory framework. We begin by laying out the baseline framework with rational expectations (subsection 6.3.1) and solving it (subsection 6.3.2). Then, we consider an augmented rational expectations model with financial frictions (subsection 6.3.3). Next, we consider diagnostic expectations (subsection 6.3.4). After that, we proceed with a quantitative evaluation of these models, by presenting impulse response functions and a calibration (subsection 6.3.5). Finally, we take stock of the theory and we develop further empirical predictions to distinguish among the theories (subsection 6.3.6), to be taken to the data.

6.3.1. Baseline framework with rational expectations

Consider a firm run by a risk-neutral owner with an infinite horizon, who discounts the future by a factor $\beta < 1$. The firm's output in period 1 is obtained by combining capital, K, and labor, L, using a constant returns to scale production function, $A_t K_t^{\alpha} L_t^{1-\alpha}$, with $\alpha < 1$. At the beginning of period t, the owner hires labor L_t at wage ω_t and makes decisions about investment during the period, I_t. The firm's optimal policy in year t maximizes the expected present value of earnings:

$$\max_{\{I_s, L_s, K_{s+1}\}_{s=t}^{\infty}} \mathbb{E}_t \left\{ \sum_{s \geq t}^{\infty} \beta^{s-t} \left[A_s K_s^{\alpha} L_s^{1-\alpha} - \omega_s L_s - I_s - C\left(I_s, K_s\right) K_s \right] \right\}$$

subject to the capital accumulation equation, $K_{s+1} = (1-\delta) K_s + I_s$, where δ denotes depreciation. We assume the commonly used quadratic investment adjustment costs:

$$C\left(I_s, K_s\right) = \frac{\chi}{2} \left(\frac{I_s}{K_s} - \delta \right)^2$$

which allow for convex adjustment costs ($\chi > 0$) as long as the $\frac{I_s}{K_s}$ ratio differs from its steady state value, δ, and displays constant returns to scale. In the maximization problem above, the operator $\mathbb{E}_t\left(.\right)$ denotes the owner's expectations conditional on available information at the beginning of year t, computed according to possibly biased beliefs. We allow for departures from rational expectations but restrict the analysis to beliefs that preserve the law of iterated expectations.

6.3.2. *Solution of baseline model*

The Lagrangian is

$$\mathcal{L} = \mathbb{E}_t \left\{ \sum_{s \geq t}^{\infty} \beta^{s-t} \left[A_s K_s^{\alpha} L_s^{1-\alpha} - \omega_s L_s - I_s - C\left(I_s, K_s\right) K_s - q_s \left(K_{s+1} - I_s - (1-\delta) K_s\right) \right] \right\}$$

and the first order conditions are:

$$\frac{\partial \mathcal{L}}{\partial L_t} = 0 \Leftrightarrow \qquad (1-\alpha) A_t K_t^{\alpha} L_t^{-\alpha} = \omega_t \tag{2}$$

$$\frac{\partial \mathcal{L}}{\partial I_t} = 0 \Leftrightarrow \qquad q_t - 1 - \chi \left(\tfrac{I_t}{K_t} - \delta \right) = 0 \tag{3}$$

$$\frac{\partial \mathcal{L}}{\partial K_{t+1}} = 0 \Leftrightarrow \quad q_t = \beta \mathbb{E}_t \left[\alpha A_{t+1} K_{t+1}^{\alpha-1} L_{t+1}^{1-\alpha} + \chi \tfrac{I_{t+1}}{K_{t+1}} \left(\tfrac{I_{t+1}}{K_{t+1}} - \delta \right) - \tfrac{\chi}{2} \left(\tfrac{I_{t+1}}{K_{t+1}} - \delta \right)^2 + q_{t+1} (1-\delta) \right] \tag{4}$$

$$TV \Leftrightarrow \qquad \lim_{T \longrightarrow \infty} \beta^T \mathbb{E}_t \left[q_{t+T} K_{t+T+1} \right] = 0$$

Then, we multiply both sides of equation (4) by current capital stock, K_{t+1}; we use the capital accumulation equation $K_{t+1} = \frac{K_{t+2} - I_{t+1}}{(1-\delta)}$ to replace K_{t+1} in front of q_{t+1}; and exploit constant returns to scale in output and investment costs. Under the standard definition of profits, $\Pi_t = A_t K_t^{\alpha} L_t^{1-\alpha} - \omega_t L_t - C\left(I_t, K_t\right) K_t - I_t$, we obtain the stochastic difference equation

$$K_{t+1} q_t = \beta \mathbb{E}_t \left[\Pi_{t+1} + K_{t+2} q_{t+1} \right]$$

After iterating forward and imposing the transversality condition, we obtain the standard investment equation:

$$\frac{I_t}{K_t} = \delta - \frac{1}{\chi} + \frac{\beta}{\chi} \frac{\mathbb{E}_t \left[\sum_{s \geq t+1}^{\infty} \beta^{s-(t+1)} \Pi_s \right]}{K_{t+1}} \tag{5}$$

In Appendix A we report the full solution of the baseline model with rational expectations, including the steady state values of all variables.

6.3.3. *Baseline model augmented with financial frictions*

Next, we introduce financial frictions. As a starting point, we begin by Kiyotaki and Moore (1997), who introduced the concept of borrowing under collateral constraints, which is now popular in many applications. Specifically, we explicitly introduce borrowing, B_t, as an additional choice variable. Borrowing an amount B_t generates tax advantages τB_t. As a result, absent constraints the firm would want to borrow and set a capital structure with 100% debt. On the other hand, borrowing is constrained by the liquidation value of its physical assets. Specifically, we model collateral constraints by introducing a cost of borrowing, $C^D(B_s, K_s)$, as follows:

$$C^D(B_s, K_s) = \phi_0 e^{-\phi_1 \cdot \left(\frac{\eta K_s}{B_s} - 1\right)}$$

where η is the liquidation value of collateral as a fraction of its book value, K, with $\eta < (1 - \delta)$: distressed capital is thus sold at a discount, as in Shleifer and Vishny (1992).

This cost formulation (used in Croce et al (2012) among others) convexifies the occasionally non-binding collateral constraint $B_t \leq \eta K_t$, which allows the firm to borrow up to the value of its collateral, i.e., the liquidation value of its capital stock. In this formulation, the parameter ϕ_1 is set (very) high to discourage the firm from borrowing more than the collateral value. The parameter ϕ_0 is accordingly set (very) low so that the firm will choose $B_t = \eta K_t$ at the steady state. By modeling this constraint as a continuous and differentiable function, we can solve the model with standard numerical methods. We present the solution of the model with rational expectations and financial frictions in Appendix B.

6.3.4. Rational vs biased expectations: An illustration

With regard to diagnostic expectations, we note that introducing diagnostic expectations in our setting generates additional cross-sectional predictions, relating forecast revisions and forecast errors to corporate investment and corporate borrowing. To see this, we begin by approximating equation (5) by

$$i_t = b_0 + b_1 \mathbb{E}_t(\pi_{t+1}) \tag{6}$$

where lowercase letters indicate scaling by capital stock, i.e., $\mathbb{E}_t(\pi_{t+1}) = \frac{\mathbb{E}_t[\Pi_{t+1}]}{K_{t+1}}$ and $i_t = \frac{I_t}{K_t}$. This approximation is reliable if expectations about the level of future earnings display significant persistence, namely $\frac{\mathbb{E}_t[\Pi_{t+1}]}{K_{t+1}}$ is not too far from $\frac{\mathbb{E}_t[\Pi_{t+2}]}{K_{t+2}}$ and more generally from earnings far away in the future. Assume now that profits follow an $AR(1)$ model such that $\pi_{t+1} = \rho \pi_t + \epsilon_{t+1}$ and

$\mathbb{E}_t(\pi_{t+1}) = \rho\pi_t$. By substituting into equation (6) and assuming rational expectations, we obtain

$$i_t = b_0(1-\rho) + \rho i_{t-1} + b_1\rho\epsilon_t$$

which implies that an $AR(1)$ process for π_t translates into an $AR(1)$ process for i_t.

Now consider biased expectations. In particular, consider the diagnostic expectations formulation of Bordalo, Gennaioli, and Shleifer (2018)

$$\mathbb{E}_t^\theta(\pi_{t+1}) = \mathbb{E}_t(\pi_{t+1}) + \theta[\mathbb{E}_t(\pi_{t+1}) - \mathbb{E}_{t-1}(\pi_{t+1})]$$

Under diagnostic expectations, it is then possible to show that

$$i_t = b_0(1-\rho) + \rho i_{t-1} + b_1\rho(1+\theta)\epsilon_t - b_1\theta\rho^2\epsilon_{t-1}$$

Under diagnostic expectations, an $AR(1)$ process in π does not translate into an $AR(1)$ process in i_t. The reason is that diagnostic expectations introduce a moving average component, so that a positive realized shock to π, ϵ_t, translates into a positive spike in i_{t+1} and also into a reversal in i_{t+2}. In other words, for $\theta = 0$, we are back to the rational expectations case, and an $AR(1)$ process in π translates into an $AR(1)$ process in i_t. For $\theta > 0$, a moving average component appears, i.e., the term multiplying ϵ_{t-1}. As a result, we have both a larger investment boost in year 1 and a reversal in year 2.

Following the same logic of Bordalo, Gennaioli, and Shleifer (2018) we can then formulate additional testable implications from the diagnostic expectations model. Define the forecast error at time $t+k$ as $\mathbb{E}_t\left[\pi_{t+k} - \mathbb{E}_t^\theta(\pi_{t+k})\right]$ (realized profits minus predicted profits, where the prediction is subject to bias θ), and the revision of expectations about profits π at time $t+k$, $0 < k < T$, as $\mathbb{E}_t\left[\mathbb{E}_{t+k}^\theta(\pi_{t+T}) - \mathbb{E}_t^\theta(\pi_{t+T})\right]$ (forecast made at time $t+k$ minus forecast made at time t). Then, it is possible to show that both forecast errors and forecast revisions at time $t+k$ are predictable in light of information held at time t. In particular, we show in Appendix C that the revision of forecasts, $\mathbb{E}_t\left[i_{t+1} - \mathbb{E}_t^\theta(i_{t+1})\right]$, is such that

$$\mathbb{E}_t\left[i_{t+1} - \mathbb{E}_t^\theta(i_{t+1})\right] = -b_1\theta\rho^2\epsilon_t$$

Thus, positive news about profits today make the firm invest more tomorrow and increase predicted profits tomorrow. However, the realized profits tomorrow are systematically smaller than predicted. Similarly, we can derive

$$\mathbb{E}_t\left[\mathbb{E}_{t+k}^{\theta}\left(i_{t+T}\right)-\mathbb{E}_t^{\theta}\left(i_{t+T}\right)\right]=-b_1\theta\rho^{T+1}\epsilon_t$$

Again, positive news today about profits today increase expected profits in the future, and these expectations systematically stear away from realized profits going forward.

6.3.5. Calibration

To calibrate the theoretical models discussed above and make them comparable to our empirical setting, we begin by abstracting from labor. Namely, we impose $L_t=\overline{L}=1$ for all t. Then, we use $\alpha=0.7$ (as commonly in settings with only capital and no labor), $\delta=0.15$, $\chi=1$, interest rate $r=0.04$ and discount factor $\beta=1/\left(1+r\right)$. We assume productivity follows an $AR\left(1\right)$ process in logs, $\ln\left[A_t\right]=\rho\ln\left[A_{t-1}\right]+\epsilon_t$, with $\epsilon_t\sim N\left(0,\sigma^2\right)$, $\rho\in[0,1]$, where we take $\rho=0.5$ and $\sigma=0.05$. Throughout this section, we produce impulse response functions and model-generated moments using the Generalized Stochastic Simulation Algorithm (GSSA) developed by Judd et al (2011).

Figure 6 reports the impulse response function of the baseline neoclassical Q-theory model with rational expectations (RE). It shows that investment, I, and capital, K, respond immediately in the first period to a shock to productivity. Then, as the shock dies out, the level of investment and capital decrease, but not instantaneously, due to the presence of adjustment costs. The direct mapping with our regression results can be done by looking at the ratio, I/K, which also responds positively in the first period and then decreases. Interestingly, after a few periods (three in our calibration), the ratio I/K turns negative. That is, the firm still invests a positive quantity, $I>0$, but lower than the depreciation rate of capital, δ, which in our parameterization represents also the steady state value of I/K. As a result, $0<I<\delta K$, and the firm becomes smaller. After that, the ratio I/K converges back to its steady state level.[22]

This pattern already rationalizes, in a qualitative sense, the empirical pattern documented in

[22]Interestingly, the fact that the baseline Q-theory presents this pattern whereby I/K crosses the steady state level and then converges to it from below crucially depends on not having labor in the model. Intuitively, in the absence of labor adjustment costs, labor adjusts faster than capital absorbing much of the overall response of the firm to the exogenous shock. As a result, I/K converges to its steady state level, δ, from above.

our regression results. However, as it is common in frictionless models, the magnitude of the effects is tiny. We then consider two ways to augment this standard neoclassical model to generate larger fluctuations. First, we introduce a financial friction, and second, we consider a specific form of biased expectations, namely diagnostic expectations.

We begin by relaxing the assumption of rational expectations and introduce diagnostic expectations, because this formulation entails a straightforward modification of the baseline Q-theory. Denoting $a_t = \ln(A_t)$, we define diagnostic expectations of productivity, A_{t+1}, as follows, consistent with Bordalo, Gennaioli, and Shleifer (2018):

$$\mathbb{E}_t^{\theta}[a_{t+1}] = \mathbb{E}_t[a_{t+1}] + \theta\left(\mathbb{E}_t[a_{t+1}] - \mathbb{E}_{t-1}[a_{t+1}]\right)$$

We use this specification because it has a number of convenient features. First, it nests rational expectations as a special case when $\theta = 0$. Second, it implies over-extrapolation of fundamentals when $\theta > 0$, consistent with psychological evidence. Third, it is a forward-looking formulation that preserves the law of iterated expectations. Fourth, as a result of the above it is immune to the Lucas critique. Fifth, it is a portable model of expectation formation in the sense of Rabin (2013).

As we have seen in Section 6.3.4 above, under diagnostic expectations if productivity, a_{t+1}, truly follows a stochastic $AR(1)$ process, then it is perceived by the agents to follow an $ARMA(1,1)$ process instead. For our calibration, we use $\theta = 0.6$, motivated by the evidence in Bordalo, Gennaioli, and Shleifer (2018) who estimate θ and find that in many cases of practical relevance, $\theta \in [0.5, 1]$. Figure 7 reports the IRFs under both rational expectations and diagnostic expectations and shows that, relative to rational expectations, diagnostic expectations produce larger swings in the variables, This occurs both in the short term in which investment, capital, and the I/K ratio respond more positively under diagnostic expectations than under rational expectations, and in the longer run, in which there is a larger reversal under diagnostic expectations than under rational expectations. Remarkably, we note that even a relatively small deviation from rational expectations (i.e., $\theta = 0.6$) produces large responses in investment, capital, and I/K, even assuming a relatively low persistence of the productivity shock, $\rho = 0.5$.[23]

Regarding the rational expectations model with financial frictions, in our calibration, we choose

[23] Typical calibrations of Q-theory under rational expectations rely on much more persistent shocks, e.g., see Cao, Lorenzoni, and Walentin (2018) who use $\rho = 0.75$.

$\eta = 0.33$, $\tau = 0.35$, and η =2000, as is common in this literature (e.g., see Croce et al (2012)). Figure 8 shows the impulse response function of the Q-theory model under rational expectations, both without collateral constraint and with the collateral constraint. Introducing collateral constraints generates larger fluctuations relative to the baseline rational expectations setting, both in the short term and in the longer run. Figure 10 then brings all three settings together to facilitate comparison.[24]

As these figures show, both financial frictions and diagnostic expectations successfully generate larger fluctuations than the baseline frictionless model with rational expectations. To disentangle the mechanisms at play in the data, in what follows we further examine in the data the empirical predictions of the financial frictions model and of the diagnostic expectations model.

6.3.6. Further empirical predictions

To further explore the mechanisms at work in our data, we develop additional cross-sectional implications of the rational expectation model with financial frictions and of the diagnostic expectations model. This seeks to sharpen our understanding of the economic channel driving our results.

We note that, irrespective of the exact form of the financial friction chosen, a common prediction of these models is that the same financial friction that generates the short term amplification should also generate the longer term reversal. We test this prediction in our data, and our findings, reported in Table 9, show that there are large and statistically significant reversals across the board, both in high financial constraints and low financial constraints firms. Even firms with low or no financial frictions exhibit a large and significant reversal in corporate investment and borrowing, similar to the reversal experienced by firms facing large financial frictions. Therefore, we conclude that a financial frictions story, while helpful in understanding the differentially larger short term impact of a credit shock on corporate investment, cannot by itself uniquely shape our understanding of financial and economic fluctuations.

[24]Once more, we should stress that ours is not a quantitative exercise. Namely, we do not want to determine whether, under "reasonable parameter values" however defined, financial frictions or diagnostic expectations generate larger fluctuations. Our purpose is to use this framework to derive further predictions to take to the data.

7. Biased Expectations and Investment

In this section, we explore the mechanism through which reversals in the real effects of credit market sentiment occur in the data. Bordalo, Gennaioli, and Shleifer (2018) hypothesize that investor over-extrapolation generates predictable mean reversion in credit market sentiment, explaining why issuer quality deterioration and the widening of credit spreads are followed by low or even negative bond returns. They provide supportive evidence for their mechanism using direct measures of investor expectation formation and show that, in the aggregate, larger forecast revisions predict lower future credit spreads. In our framework, we expect that the pattern of high investment in year $t+1$ and low investment in years $t+4$ and $t+5$ to be more pronounced among firms with larger forecast revisions; and we also expect this pattern to come with larger forecast errors.

We assess this mechanism empirically in the cross section of firms. In our setting, according to the theory of Bordalo, Gennaioli, and Shleifer (2018), we expect that firms for which equity analysts exhibit larger earnings forecast revisions should experience (i) larger reversals in corporate investment, (ii) larger reversals in total net debt issuance, and (iii) larger realized negative forecast errors. In Table 11, we test prediction (i) for corporate investment. Panel A shows the effect of credit market sentiment in year t on investment in year $t+1$ to $t+5$ for firms in the top decile of analyst forecast revisions in year t. Panel B reports the same effects for firms in the bottom decile of analyst forecast revisions. Consistent with over-extrapolation, we find that in response to credit market sentiment in year t, firms in the top decile of analyst forecast revisions exhibit both a higher positive effect on investment in year $t+1$ and a higher reversal (i.e., a more negative effect) on investment in years $t+4$ and $t+5$ relative to firms in the bottom decile of analyst forecast revisions. Panel C shows that the difference between top and bottom decile is negative in years $t+4$ and $t+5$ and strongly statistically significant in year $t+4$. Table 12 reports similar effects for total net debt issuance, consistent with prediction (ii). Specifically, in the face of higher credit market sentiment, firms with the highest forecast revisions in year t (Panel A) exhibit a stronger positive effect on debt issuance in year $t+1$ and a more negative effect in years $t+4$ and $t+5$ than firms with the lowest forecast revisions (Panel B). Panel C shows that the difference between top and bottom decile is positive and significant in year $t+1$. Then it turns negative and strongly statistically significant in years $t+4$ and $t+5$.

To examine prediction (iii), we measure analyst forecast errors as the difference between actual EPS in fiscal year $t+k$ minus the last consensus forecast for that same number made in fiscal year t. This difference is then normalized by the stock price two days before the forecast was made. In Table 13, we use analyst forecast errors as the dependent variable and estimate a version of equation (1), where we interact the credit market sentiment variable with analyst forecast revisions (as used in Tables 11 and 12). Each column stands for a different value of k from 1 to 5. We find that forecast revisions predict forecast errors positively in year 1 and negatively in years 4 and 5, consistent with Bordalo, Gennaioli, and Shleifer (2018). Crucially, following a credit market boom, firms with higher forecast revisions at time t have significantly more negative forecast errors at time $t+5$. The evidence thus supports an expectations-driven business cycle, whereby following a credit market shock in year t, biased expectations drive investment to respond excessively in year $t+1$. After realizations cause a revision of forecasts, firms find themselves with an excessive capital stock and start reducing it in years $t+4$ and $t+5$.

We conclude this section by providing a quantitative evaluation of the theoretical models reviewed in Section 6.3.5 above. To do so, we first report the first and second empirical moments in our data on the main variables of our analysis, namely investment, profitability, leverage, forecast revisions, and forecast errors.[25] We then compare those empirical moments with the same moments as generated by the theoretical models considered, namely the RE model, the rational expectations benchmark, i.e., standard Q-theory; the RE+FF model, the rational expectations model augmented by financial frictions; the DE model, the diagnostic expectations model, whereby over-extrapolation is the only deviation from the baseline RE model; and the DE+FF model, the diagnostic expectations model with financial frictions.

We report the results of our quantitative evaluation in Table 14. As it is well known, the baseline model with rational expectations, i.e., standard Q-theory, already does a good job at matching the first moments of investment and profitability, even though, as shown above, the baseline RE model does not produce large enough fluctuations in those variables. As it is also well known, the baseline RE model underestimates the second moments of all variables, and obviously does not produce estimates of leverage. In addition, we show that the RE model, by construction, produces zero

[25] Because forecast revisions and forecast errors are available at different horizons, the estimates reported are averages for the mean and standard deviation statistics calculated for each horizon. Due to data availability, we use horizons of $t+1$ to $t+4$ for forecast revisions and $t+1$ to $t+5$ for forecast errors.

forecast revisions and zero forecast errors, while the empirical moments of forecast revisions and forecast errors are negative and large.

Adding financial frictions to the baseline model with rational expectations (the RE+FF column) produces an estimate of leverage in line with the empirical moment, marginally improves on the second moment of investments, and slightly worsens on the first moment of profitability. Adding financial frictions to the baseline model with rational expectations does nothing to improve the fit of the model with respect to forecast revisions and forecast errors.

Considering the model with diagnostic expectations (the DE column), we find that it also matches the first moments of investment and profitability quite well. Furthermore, it produces a marginally larger second moment of investment, thereby marginally improving over models based on rational expectations. Crucially, and unlike models relying on rational expectations, the model with diagnostic expectations produces estimates of forecast revisions and forecast errors in line with the empirical moments. Adding financial frictions to the diagnostic expectations model (the DE+FF column) produces estimates of leverage in line with the empirical moments and slightly worsens the fit in terms of profitability, forecast revisions and forecast errors.

It is worth noting that the fact that our DE model matches the data quite well is remarkable, because in the DE model the cost of capital is constant over time, so that fluctuations in borrowing and investment are only due to expectations-driven changes in credit demand. The fluctuations would be larger–or, alternatively, one could obtain similar fluctuations with a lower value of the extrapolation parameter θ–if the model also took into account the fact that credit is mispriced, in line with the empirical evidence in Greenwood and Hanson (2013). To be sure, more research is needed to assess the extent to which credit mispricing is driven by biased expectations of fundamentals or by excessive extrapolation of past market conditions.

In sum, the results of our quantitative evaluation demonstrate that a model where over-extrapolative expectations is the only deviation from standard Q-theory does a good job matching the empirical moments of our data. In the next section, we draw the implications of our findings for theory and policy.

8. Conclusion

We have examined the real effects of credit market sentiment on corporate investment and financing decisions of a comprehensive panel of U.S. public and private firms over 1963-2016, and how the effects of credit market sentiment on investment depends on the formation and revision of expectations by financial analysts. Consistent with the Minsky hypothesis, our results show that credit market cycles beget corporate investment cycles, and the effect of credit market sentiment operates through the formation and revision of biased expectations. Good news about fundamentals make investors and managers too optimistic; in turn, optimism drives down the cost of capital too much, inducing managers to borrow and invest too much. Subsequently, systematic disappointment triggers abrupt reversals in both credit and investment.

What are the implications of our results for economic policy? In the short run, a credit market boom in year t accompanies subsequent increased investment in year $t+1$. This short-term increase in investment is predominantly confined among financially constrained firms, presumably helping bring their investment closer to the first-best level. Therefore, at first glance this evidence would seem to vindicate the view of Alan Greenspan and others that central banks should not deploy monetary policy to restrain or curb financial market prices, even when financial market valuations are significantly above fundamentals. However, our data shows that this view is incomplete.

In fact, our data suggests a much more nuanced interpretation. We find that the effects of credit market sentiment on investment eventually reverse in the years $t+4$ and $t+5$. Crucially, such reversals occur across the board, so they are not confined to a subset of financially constrained firms, but are much more pervasive and occur almost in all sectors of the economy. Furthermore, these longer-term reversals have a much larger economic magnitude than the short-term effects at time $t+1$. Therefore, because sentiment-fueled corporate investment booms give rise to longer term reversals, at a minimum, our evidence indicates that there is scope for ex post monetary policy measures to counter the dry up of liquidity and support corporate investment, providing support to the Federal Reserve and European Central Bank policies of quantitative easing following the 2007-08 financial crisis.

More generally, our results indicate that, when faced with ex ante excessively high financial market prices and in deciding whether to restrain or curb them, central banks should weigh the short term benefits of reducing under-investment of financially constrained firms against the longer term costs of corporate liquidity and investment dry ups across the board. The sheer magnitude and pervasiveness of the latter costs following the 2007-08 financial crisis indicate that a pure *laissez faire* monetary policy ex ante does trigger predictable and avoidable costs to the real economy ex post, likely in excess of any short term benefit in reducing under-investment of constrained firms.

In terms of economic theory, our results suggest a promising way forward for macroeconomics and finance research toward an integrated theory of business cycles. First, we find that in the short term, credit market sentiment has real effects on corporate investment and financing, over and above standard Q theory, consistent with a debt-financing channel. Therefore, an integrated theory of business cycles should explicitly model a debt-financing channel. Second, we find that the real effects of credit market sentiment differ across firms depending on financial constraints. Therefore, financial frictions help explain the short term amplification of productivity shocks. At the same time, financial frictions cannot uniquely shape our understanding of credit cycles and business cycles, because in the longer term there are reversals in corporate borrowing and investment for all types of firms, irrespective of financial frictions. Third, we find that the predictable mean reversion in credit market sentiment produces predictable reversals in its real effects on corporate investment and financing. Crucially, the transmission of credit market shocks to the real investment of corporations occurs through the revision of systematically biased expectations about firms fundamentals. These last pieces of evidence point to the need to incorporate a realistic theory of belief formation and revision into theories of business cycles.

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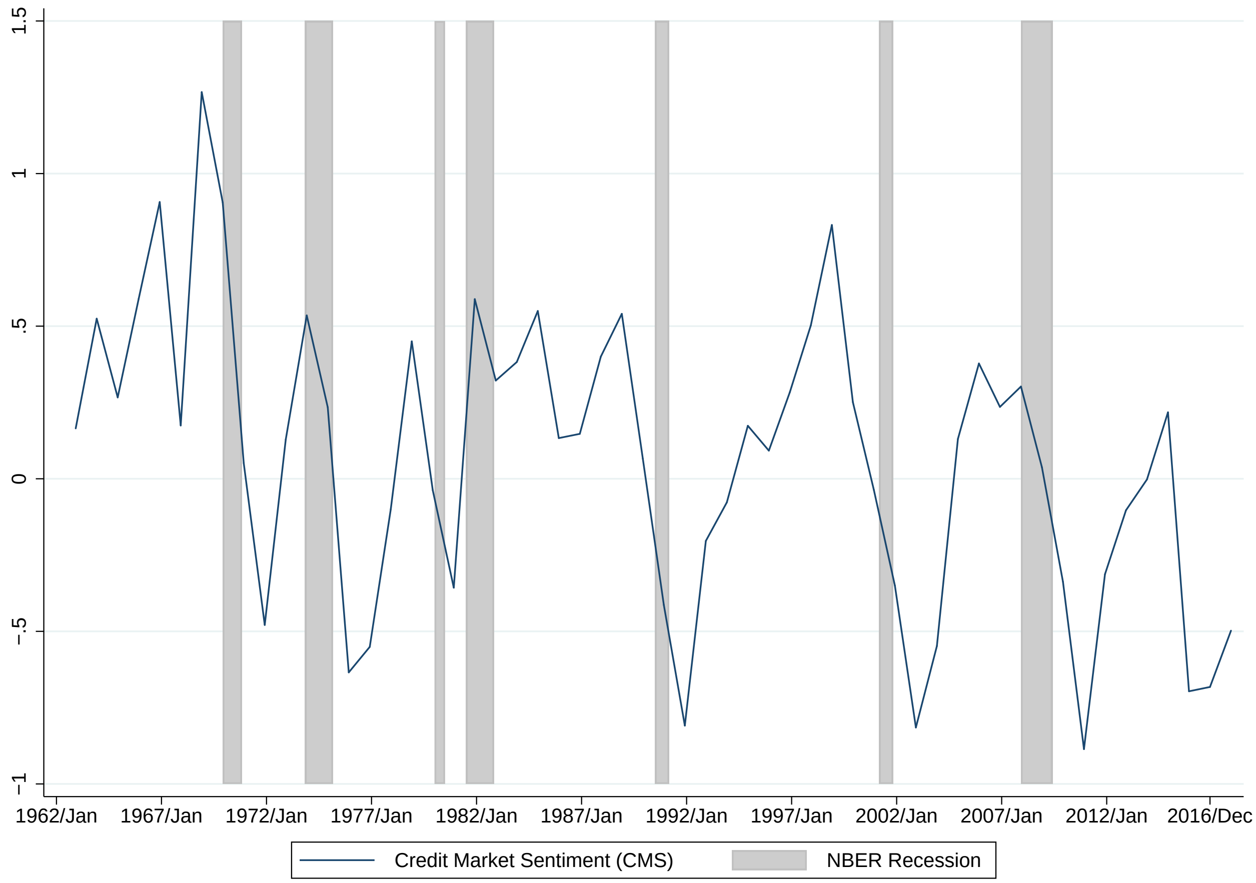

Figure 1
Credit Market Sentiment
This figure plots the credit market sentiment index of Greenwood and Hanson (2013). This index is calculated as the difference between average default probabilities of firms with the highest debt issuance and firms with the lowest debt issuance in any given year. The shaded areas are NBER recessions.

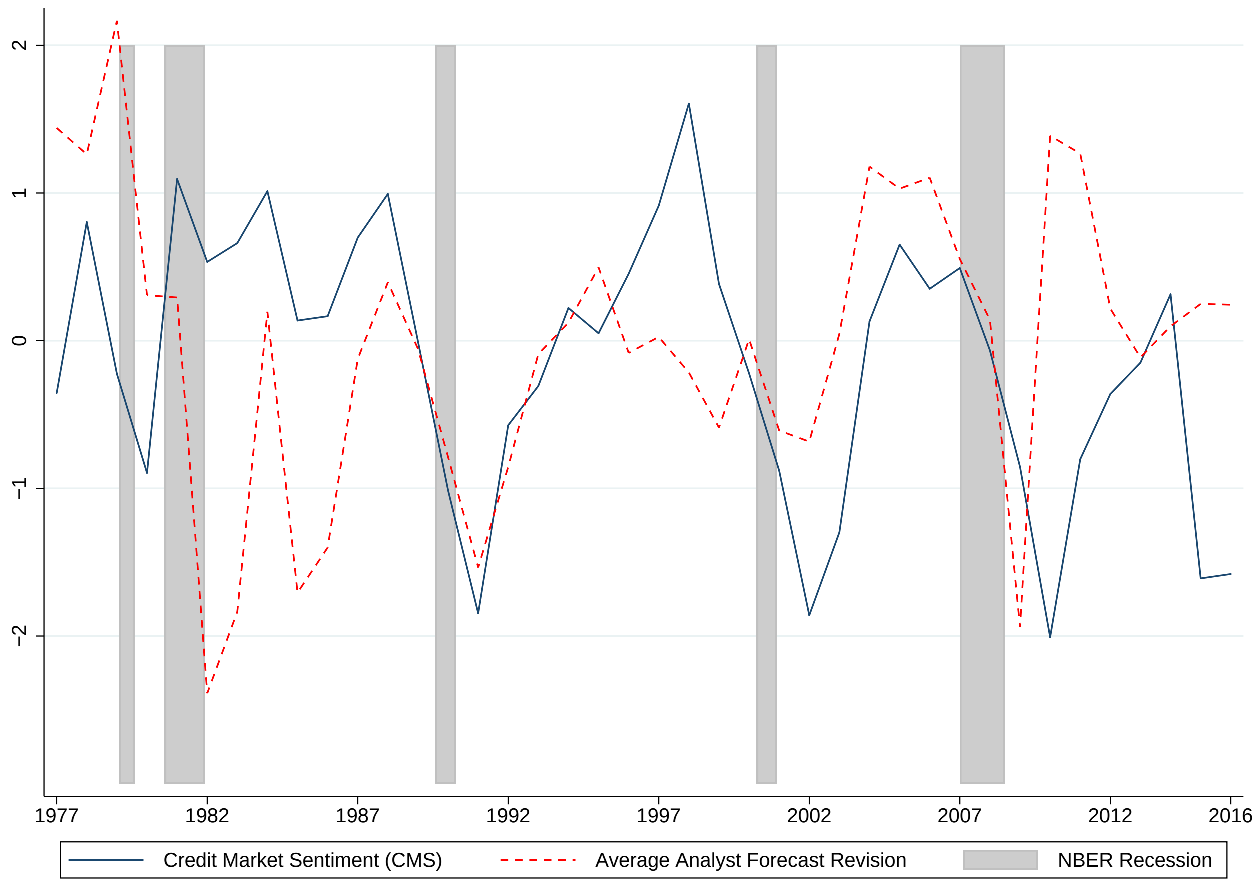

Figure 2
Credit Market Sentiment and Analyst Forecast Revisions
The solid line in this figure plots the credit market sentiment index of Greenwood and Hanson (2013). This index is calculated as the difference between average default probabilities of firms with the highest debt issuance and firms with the lowest debt issuance in any given year. The dashed line plots average analyst forecast revisions. This is calculated using data from IBES, as the series of annual cross-sectional averages of the year-over-year changes in (consensus) analyst forecasts of firm-level earnings per share. The shaded areas are NBER recessions. Regressing the credit market sentiment index on the lagged average analyst forecast revision and the macroeconomic controls in our main tests yields a coefficient of 0.324 with a t-statistic of 1.98 (p-value of 5.6%).

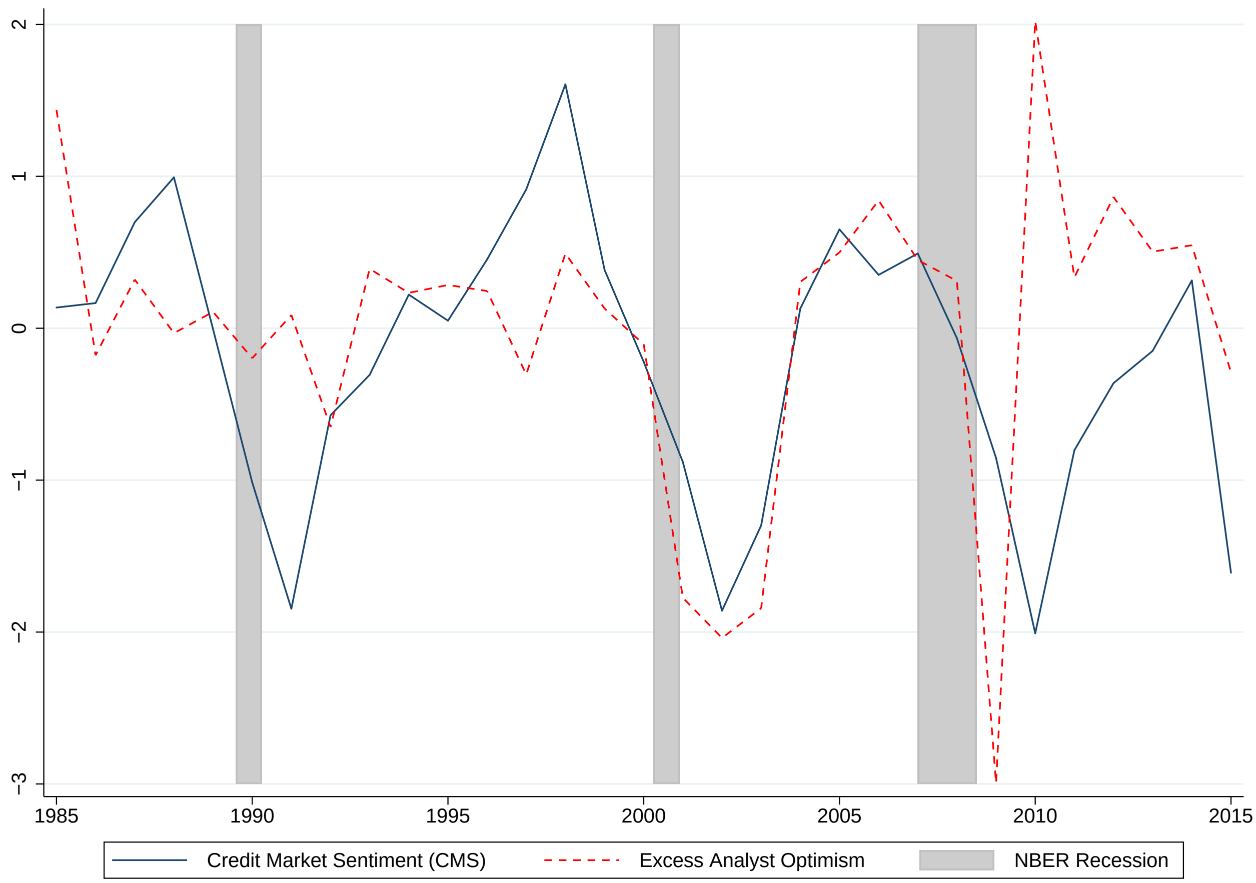

Figure 3
Credit Market Sentiment and Excess Analyst Optimism
The solid line in this figure plots the credit market sentiment index of Greenwood and Hanson (2013). The dashed line plots the average analyst (EPS) forecast of issuers of speculative-grade bonds minus the average analyst forecast of investment-grade bond issuers. The correlation between the two series is 32%. The shaded areas are NBER recessions.

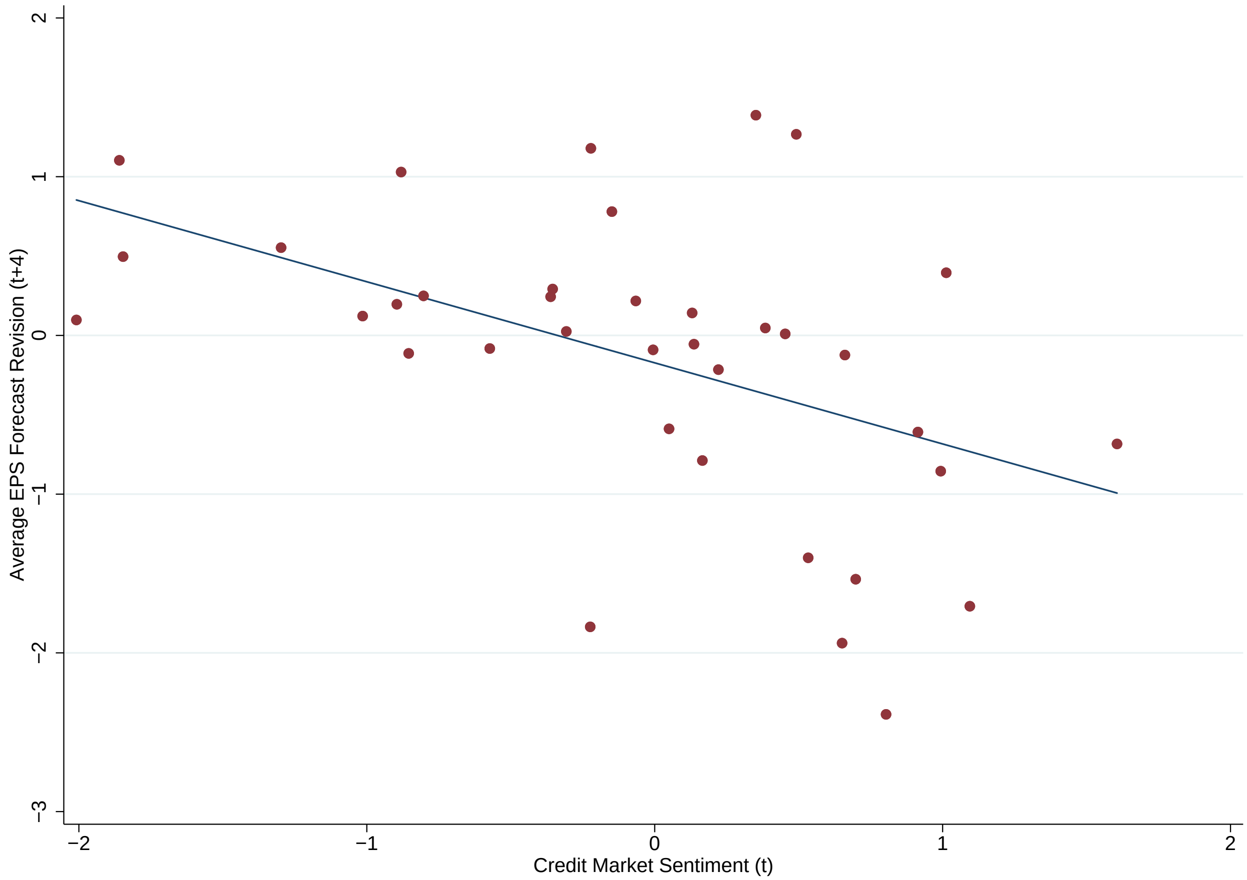

Figure 4
Credit Market Sentiment Predicts Downward Forecast Revisions
Each point on this scatter plot represents the credit market sentiment index of Greenwood and Hanson (2013) in a particular year t (horizontal axis) and the average of all analyst EPS forecast revisions in year $t+4$. The sample period is 1985 to 2015. The slope of the regression line is -0.447 with a t-statistics of -3.48.

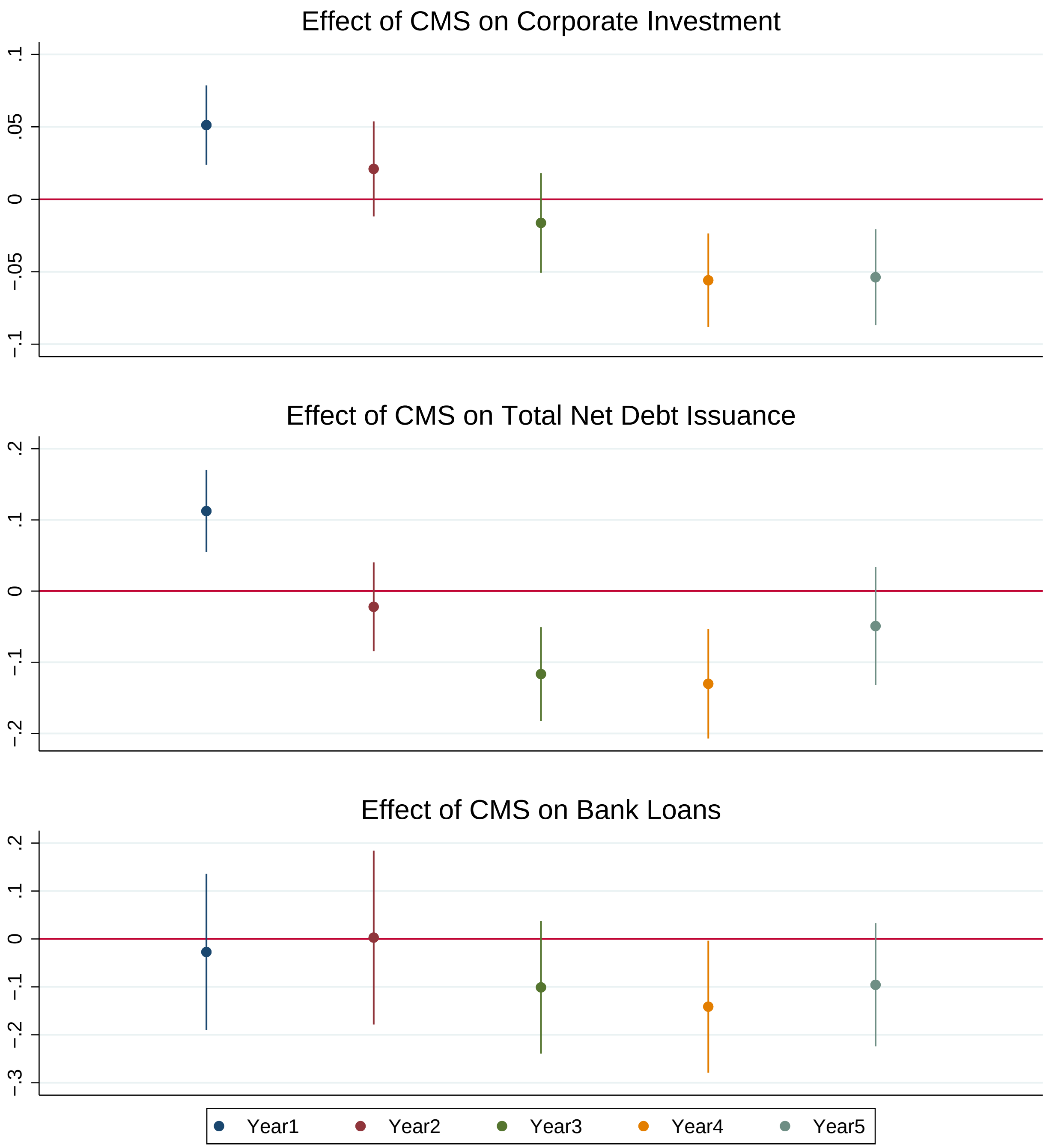

Figure 5
Effect of Credit Market Sentiment
This figure plots the coefficients on the Credit Market Sentiment Variable (CMS) when predicting future corporate investment (top panel), total net debt issuance (middle panel) and new bank loans (bottom panel). All independent variables from our baseline specification are included and are measured at time T. Year "k" (k=1...5) means the dependent variable is measured at time T+k. The economic magnitude (y axis) can be interpreted as the change (expressed as % of the mean) in the dependent variable caused by a one standard deviation increase in CMS.

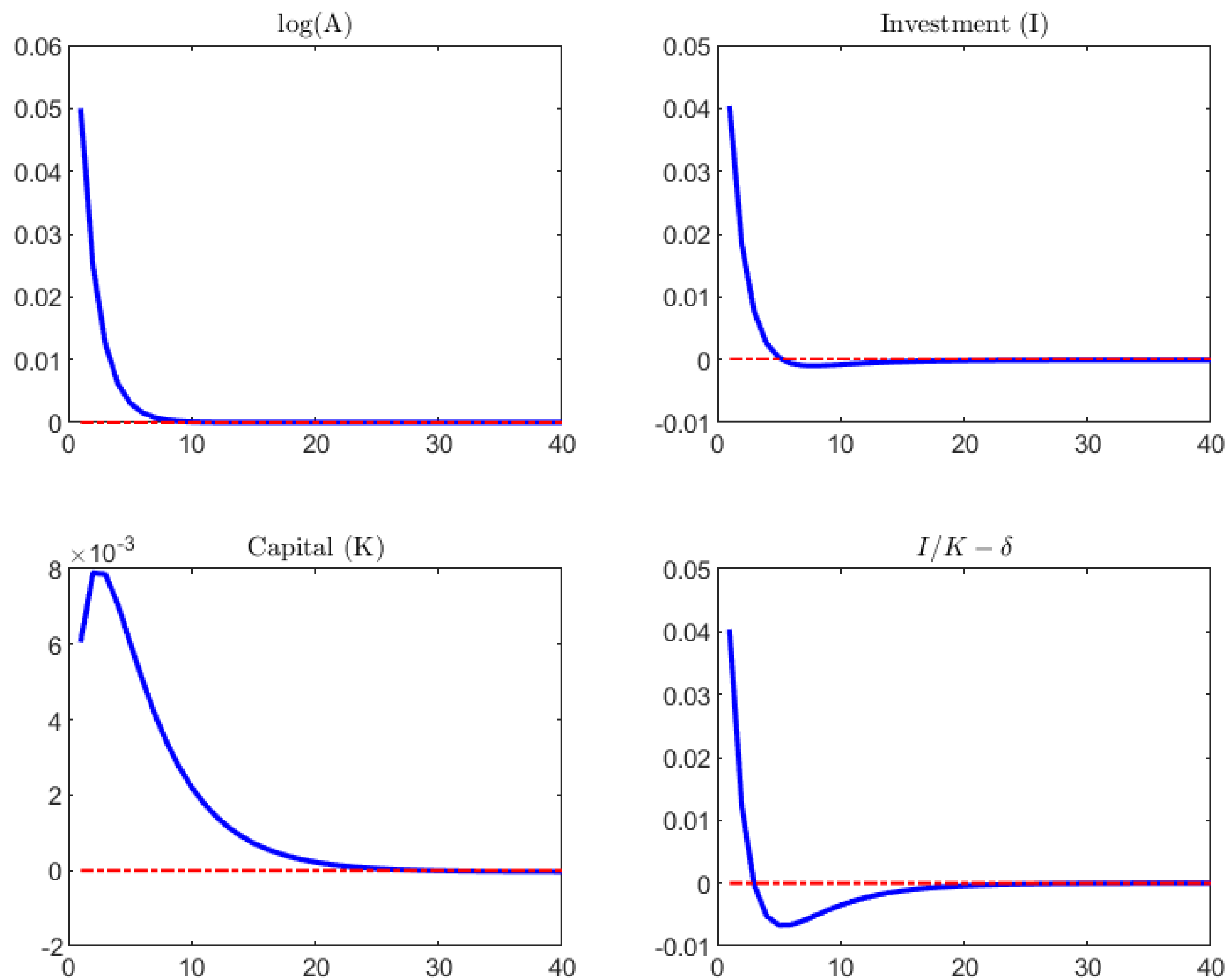

Figure 6
IRF under Rational Expectations
This figure plots the impulse response function of neoclassical Q-theory under rational expectations (RE). All variables are measured at time T=0. Year "k" (k=1...5) means the dependent variable is measured at time T+k=k. The economic magnitude (y axis) can be interpreted as the change (expressed as % of the mean) in the dependent variable caused by a one standard deviation shock to TFP. The x axis represent the steady state value of the variable.

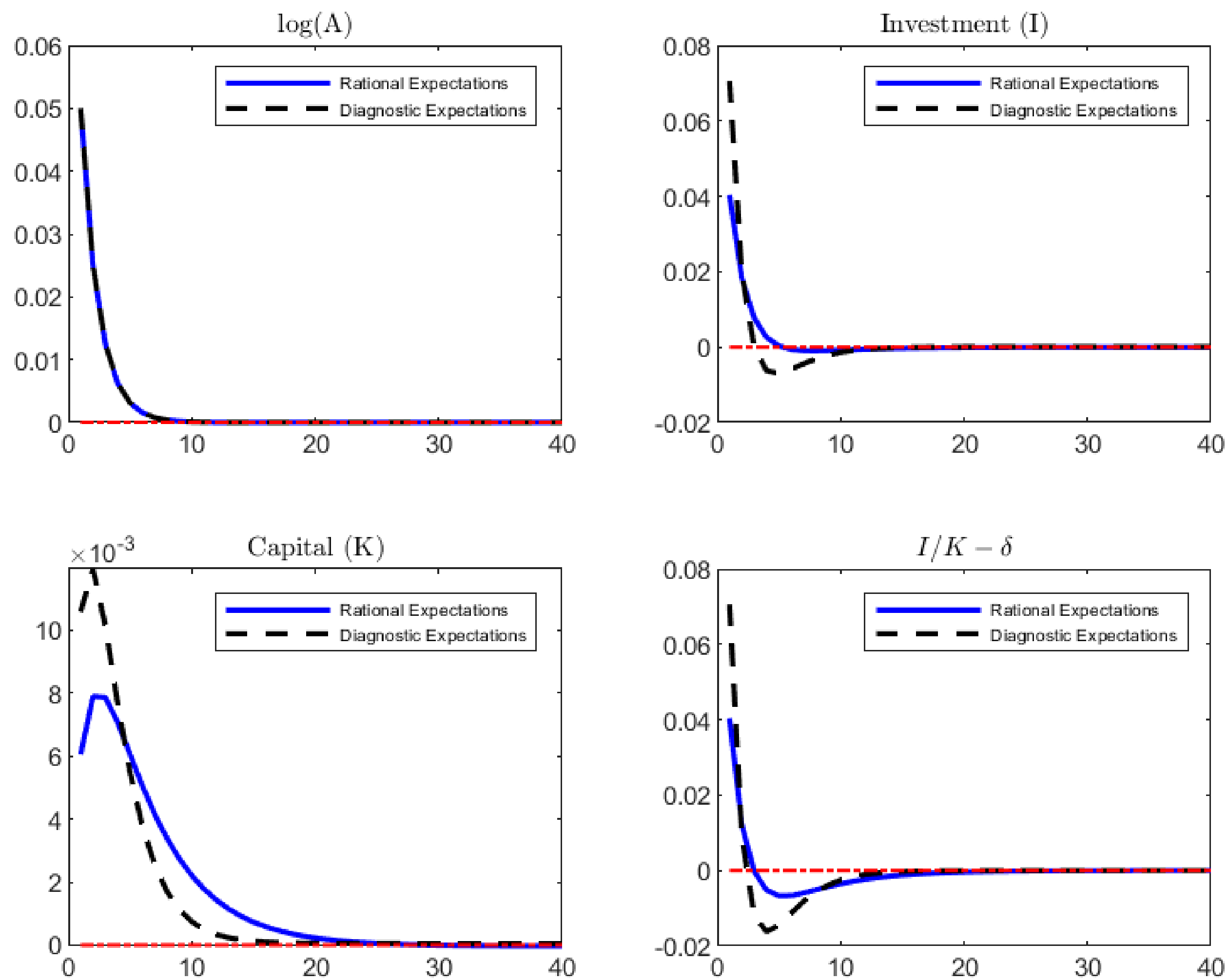

Figure 7
IRF under Rational Expectations and under Diagnostic Expectations
This figure plots the impulse response function of neoclassical Q-theory under rational expectations (RE) and of Q-theory under diagnostic expectations (DE). All variables are measured at time T=0. Year "k" (k=1...5) means the dependent variable is measured at time T+k=k. The economic magnitude (y axis) can be interpreted as the change (expressed as % of the mean) in the dependent variable caused by a one standard deviation shock to TFP. The x axis represent the steady state value of the variable.

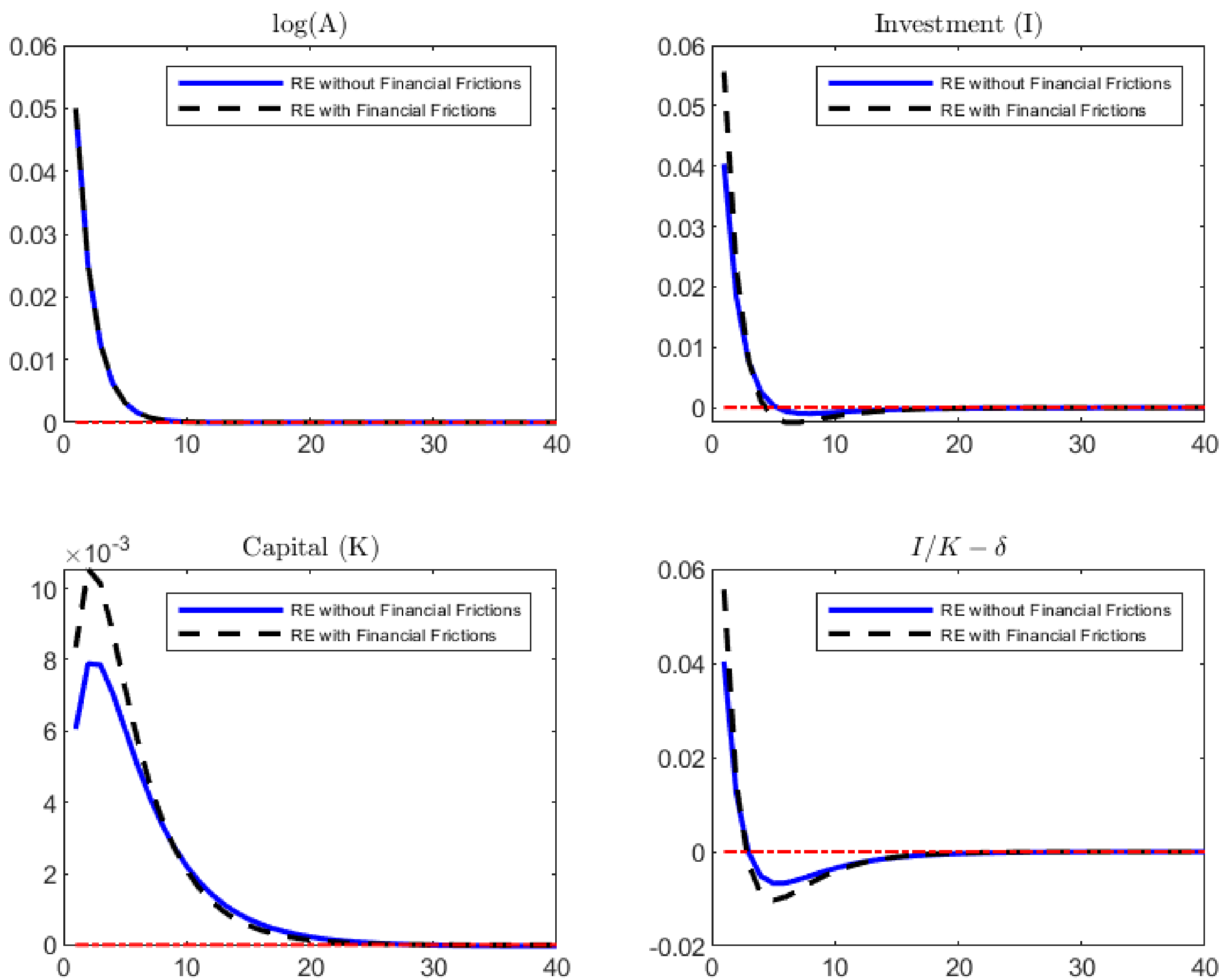

Figure 8
IRF under Rational Expectations, with and without Financial Frictions
This figure plots the impulse response function of neoclassical Q-theory under rational expectations (RE) without collateral constraint and with collateral constraint. All variables are measured at time T=0. Year "k" (k=1...5) means the dependent variable is measured at time T+k=k. The economic magnitude (y axis) can be interpreted as the change (expressed as % of the mean) in the dependent variable caused by a one standard deviation shock to TFP. The x axis represent the steady state value of the variable.

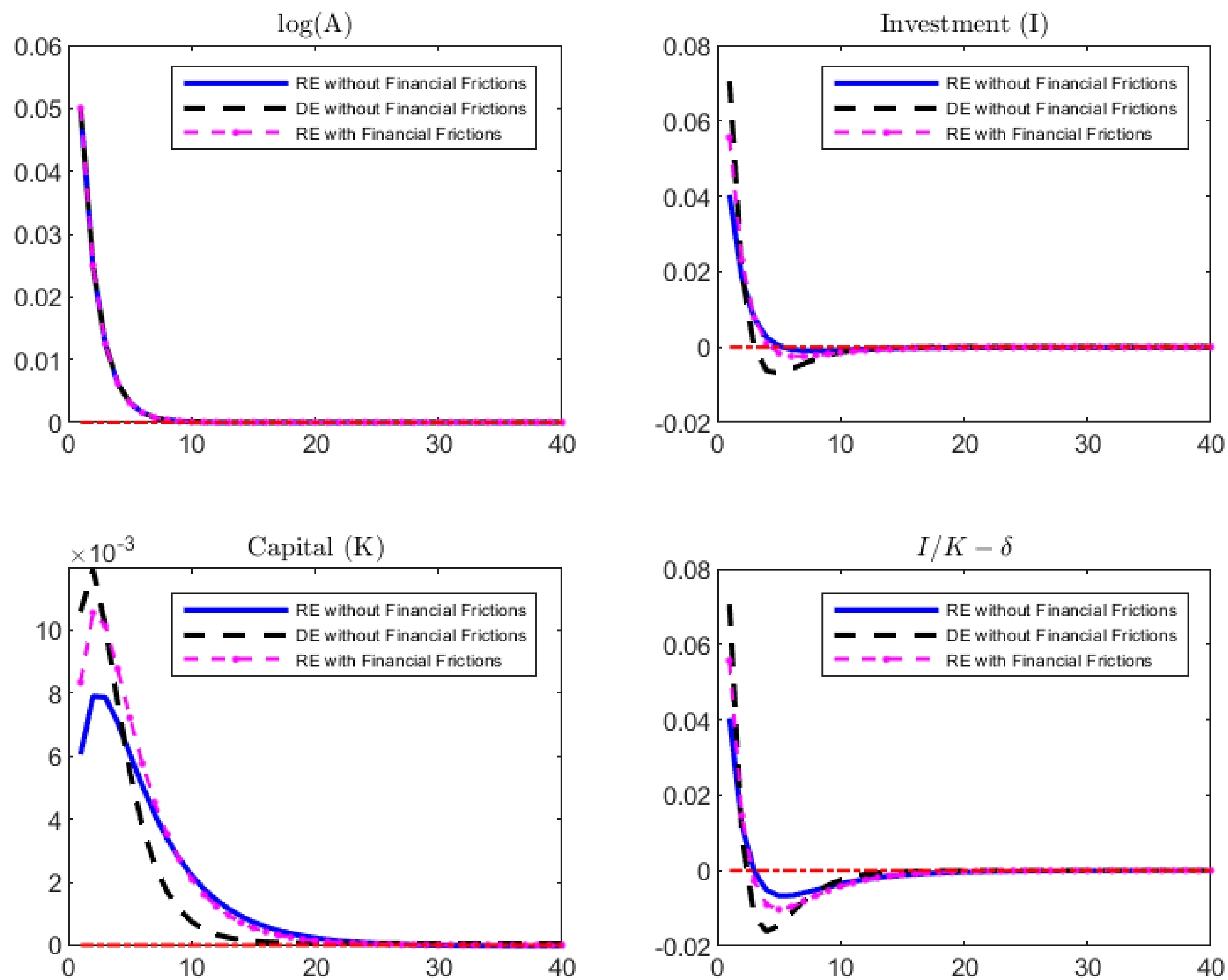

Figure 9
IRF under Rational Expectations with and without Financial Frictions, and IRF under Diagnostic Expectations
This figure plots the impulse response function of neoclassical Q-theory under rational expectations (RE) without collateral constraint and with collateral constraint, and of Q-theory with diagnostic expectations (DE). All variables are measured at time T=0. Year "k" (k=1...5) means the dependent variable is measured at time T+k=k. The economic magnitude (y axis) can be interpreted as the change (expressed as % of the mean) in the dependent variable caused by a one standard deviation shock to TFP. The x axis represent the steady state value of the variable.

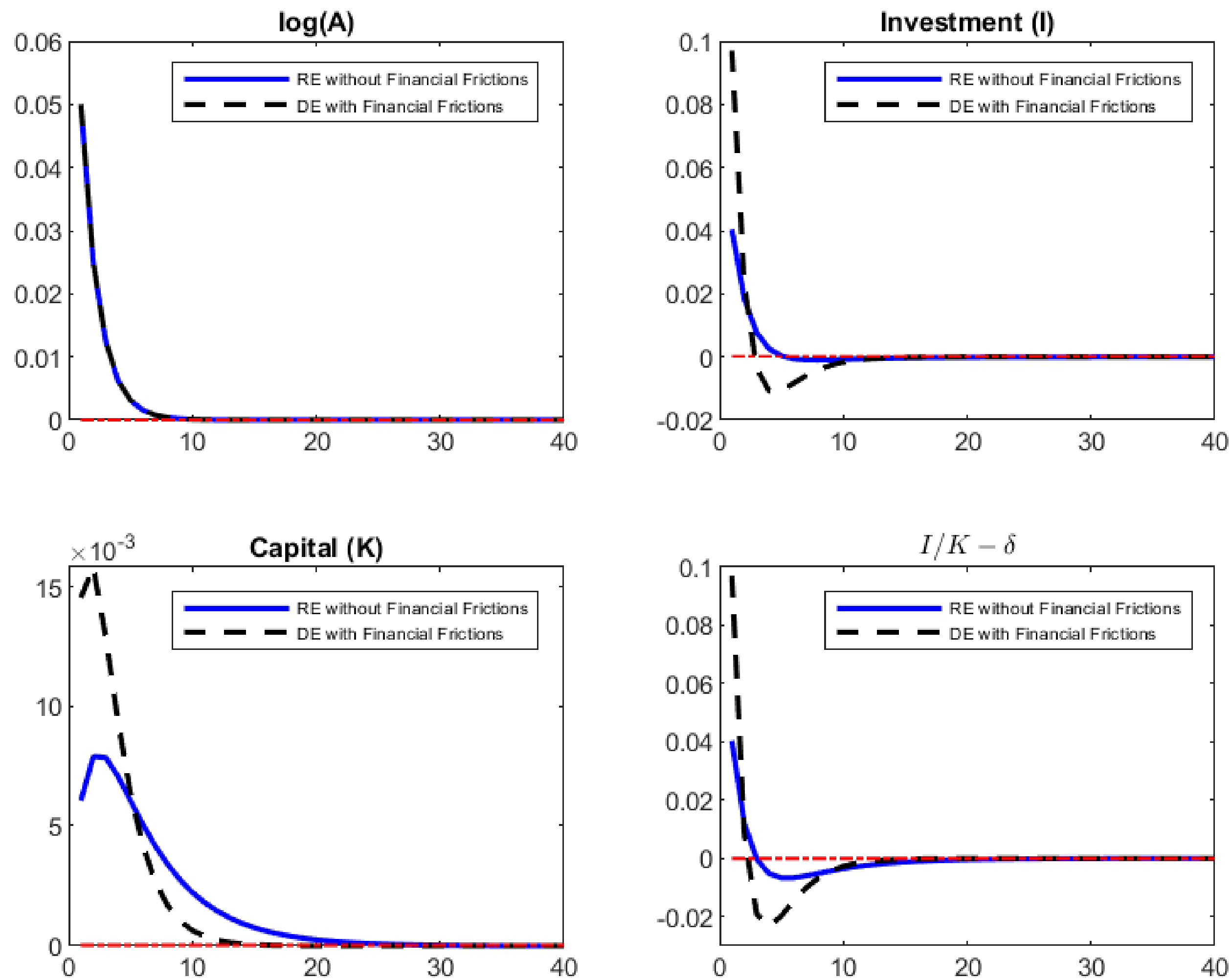

Figure 10
IRF under Rational Expectations without Financial Frictions, and IRF under Diagnostic Expectations with Financial Frictions
This figure plots the impulse response function of neoclassical Q-theory under rational expectations (RE) without collateral constraint, and of Q-theory with diagnostic expectations (DE) and collateral constraint. All variables are measured at time T=0. Year "k" (k=1...5) means the dependent variable is measured at time T+k=k. The economic magnitude (y axis) can be interpreted as the change (expressed as % of the mean) in the dependent variable caused by a one standard deviation shock to TFP. The x axis represent the steady state value of the variable.

Table 1
Summary Statistics

This table presents summary statistics for the main variables used in our analysis. The sample period is from 1963 to 2016. The investment and Tobin's Q variables are measured as in Peters and Taylor (2017). Specifically, total capital is gross PPE (i.e., physical capital) plus the sum of goodwill, capitalized R&D and capitalized SG&A (i.e., intangible capital). Total investment is the percentage change in total capital, investment in physical capital is the change in physical capital divided by lagged total capital, and investment in intangible capital is the change in intangible capital divided by lagged total capital. Tobin's Q is the market value of equity plus book value of debt divided by total capital. Total net debt issuance is the one year change in total assets minus the one year change in book equity, scaled by lagged total assets. Long-term net debt issuance is the change in long term debt ("dltt"+"dlc" in Compustat) scaled by lagged total assets. Short-term net debt issuance is total net debt issuance minus long-term net debt issuance. Credit quality is the measure of default probability developed by Bharath and Shumway (2008). The remaining variables are standard.

	N	Mean	Median	Std. dev.
Total Investment	121,217	0.184	0.104	0.323
Investment physical capital	121,217	0.088	0.043	0.178
Investment intangible capital	121,217	0.091	0.041	0.181
Total net debt issuance	121,200	0.084	0.032	0.230
Long-term net debt issuance	121,114	0.046	0.003	0.163
Short-term net debt issuance	121,104	0.037	0.019	0.103
Credit quality	121,217	0.043	0.000	0.100
Tobin's q	121,217	0.941	0.507	1.774
Cash flow to assets	121,217	0.067	0.092	0.161
Log total assets	121,217	5.708	5.597	2.000
Cash to assets	121,217	0.121	0.061	0.155
Book Leverage	121,217	0.252	0.234	0.175
Sales growth	121,217	0.179	0.100	0.459
ROA	121,217	0.052	0.087	0.182

Table 2
Correlation between Credit Market Sentiment and other Macroeconomic Conditions

This table presents the correlation coefficients between Credit Market Sentiment (CMS) and several macroeconomic variables. In Panel A we use proxies for first moment shocks: the Leading economic index from the Conference Board, the index of consumer confidence from the University of Michigan, the national activity index from the Chicago Fed, and the average GDP growth forecast from the Livingstone Survey of Professional Forecasters from the Philadelphia Fed. In Panel B we use proxies for second moment shocks: the aggregate measure of macroeconomic uncertainty from Jurado, Ludvigson, Ng (2015), the VXO index from the CBOE, and the standard deviation of GDP growth forecasts from the Livingstone Survey of Professional Forecasters from the Philadelphia Fed. In Panel C, we use proxies for sentiment in the equity market and cost of debt: Robert Shiller's cyclicality adjusted aggregate PE index (CAPE), the Baker and Wurgler (2006) investor sentiment index, the default spread, and the term spread. P-values are in parentheses.

Panel A: Correlations with macro proxies for investment opportunities

	CMS	LEI	MCC	CFNAI
Leading economic index (LEI)	-0.03			
	(0.80)			
Michigan consumer confidence(MCC)	0.33	0.38		
	(0.04)	(0.02)		
Chicago Fed national activity index (CFNAI)	0.03	0.79	0.45	
	(0.85)	(0.00)	(0.00)	
Forecasted GDP growth	-0.08	0.13	-0.27	0.20
	(0.56)	(0.38)	(0.10)	(0.17)

Panel B: Correlations with proxies for macroeconomic uncertainty

	CMS	JLN index	VXO index
Jurado, Ludvigson, Ng (JLN) index	-0.14		
	(0.32)		
VXO index	-0.09	0.65	
	(0.64)	(0.00)	
GDP growth forecast disagreement	0.09	0.50	0.63
	(0.56)	(0.00)	(0.00)

Panel C: Correlations with proxies for equity valuation and cost of debt

	CMS	Shiller PE	BW index	Default spread
Shiller's PE ratio	0.04			
	(0.77)			
Baker, Wurgler (BW) index	0.26	0.30		
	(0.07)	(0.04)		
Default spread	-0.18	-0.28	0.01	
	(0.18)	(0.02)	(0.94)	
Term spread	0.15	-0.52	0.07	0.36
	(0.26)	(0.00)	(0.65)	(0.00)

Table 3
Credit Market Sentiment and Corporate Investment

This table presents coefficient estimates from regressing total investment (columns 1 to 3), investment in physical capital (columns 4 to 6), and investment in intangible capital (columns 7 to 9) on credit market sentiment and firm-level controls. The credit market sentiment variable is measured following Greenwood and Hanson (2013) as the difference between (weighted) average default probabilities of firms with the highest debt issuance and firms with the lowest debt issuance in any given year. The investment and Tobin's Q variables are measured as in Peters and Taylor (2017). Specifically, total capital is gross PPE (i.e. physical capital) plus the sum of goodwill, capitalized R&D, and capitalized SG&A (i.e., intangible capital). Total investment is the percentage change in total capital, investment in physical capital is the change in physical capital divided by lagged total capital, and investment in intangible capital is the change in intangible capital divided by lagged total capital. Tobin's Q is the market value of equity plus book value of debt divided by total capital. In columns 3, 6, and 9, we also control for a set of macroeconomic variables (the Leading Economic Index from the Conference Board (LEI), the Jurado, Ludvigson, and Ng (2015) index of macro uncertainty (JLN), the Baker and Wurgler (2006) sentiment index (BW) and the default spread) and the Bharath and Shumway (2008) measure of credit quality. All specifications include firm fixed-effects, and standard errors are computed using Driscoll-Kraay (1998) to account for time-series correlation between error terms. *t*-statistics are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Total investment			Investment in physical capital			Investment in intangible capital		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CMS	0.061***	0.044***	0.051***	0.072***	0.052***	0.068***	0.051***	0.037***	0.038**
	(3.47)	(3.17)	(3.76)	(3.23)	(3.14)	(4.61)	(3.26)	(2.73)	(2.59)
Tobin's q	0.714***	0.602***	0.704***	0.644***	0.523***	0.642***	0.718***	0.612***	0.675***
	(39.31)	(32.27)	(32.77)	(18.20)	(18.32)	(15.11)	(20.26)	(17.38)	(18.10)
Cash flow to assets	0.238***	0.125***	0.141***	0.303***	0.176***	0.192***	0.187***	0.056**	0.076***
	(9.88)	(6.78)	(7.21)	(7.95)	(5.68)	(5.06)	(9.15)	(2.29)	(3.29)
Log total assets		-0.653***	-0.672***		-0.870***	-0.890***		-0.423***	-0.442***
		(-17.88)	(-15.37)		(-20.41)	(-17.87)		(-11.74)	(-10.35)
Cash to assets		0.280***	0.305***		0.257***	0.309***		0.267***	0.283***
		(16.74)	(15.84)		(9.42)	(10.24)		(9.76)	(9.57)
Book leverage		-0.125***	-0.105***		-0.194***	-0.157***		-0.058***	-0.056***
		(-11.95)	(-10.37)		(-14.08)	(-12.22)		(-4.59)	(-4.32)
Sales growth		0.121***	0.128***		0.125***	0.137***		0.125***	0.132***
		(11.87)	(12.99)		(9.95)	(10.12)		(12.55)	(12.25)
ROA		0.128***	0.091***		0.143***	0.121***		0.151***	0.099***
		(8.14)	(5.36)		(6.02)	(4.04)		(8.81)	(6.02)
LEI			-0.035**			-0.036*			-0.031*
			(-2.11)			(-1.72)			(-1.87)
JLN index			0.020			-0.000			0.038**
			(1.09)			(-0.01)			(2.58)
BW index			-0.056***			-0.068***			-0.044***
			(-4.29)			(-3.49)			(-3.79)
Default spread			-0.059***			-0.030*			-0.084***
			(-4.62)			(-1.97)			(-6.50)
Credit quality			-0.101***			-0.156***			-0.050***
			(-6.34)			(-8.48)			(-3.13)
Constant	0.897***	0.940***	1.071***	0.899***	0.957***	1.135***	0.902***	0.925***	1.006***
	(38.96)	(54.04)	(62.82)	(29.98)	(45.50)	(46.95)	(43.38)	(50.19)	(51.93)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	137,246	135,271	115,827	137,277	135,302	115,856	137,517	135,525	116,025
R^2	0.122	0.167	0.182	0.078	0.128	0.146	0.099	0.121	0.121

Table 4
Conditioning on Financial Constraints

This table presents coefficient estimates from regressing total investment (Panel A) and net debt issuance (Panel B) on credit market sentiment (measured as in Greenwood and Hanson (2013)) and various measures of financial constraints (the Hadlock and Pierce (2010) index in the first three columns, the Whited and Wu (2006) index in the middle three columns, and an indicator that equals one if the firm has never had a credit rating, in the last three columns). All specifications include firm fixed-effects, firm-level controls (Tobin's Q, Cash flow to assets, Log total assets, Cash to assets, Book leverage, Sales growth, ROA) and macro-level controls (the Leading Economic Index from the Conference Board, the Jurado, Ludvigson, and Ng (2015) index of macro uncertainty, the Baker and Wurgler (2006) sentiment index, and the default spread). Standard errors are computed using Driscoll-Kraay (1998) to account for time-series correlation between error terms. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Dependent variable is total corporate investment								
	Bottom HP tercile	Top HP tercile	Top and bottom HP terciles	Bottom WW tercile	Top WW tercile	Top and bottom HP terciles	With credit rating	Without credit rating	Full sample
CMS	0.025	0.068***	0.026*	0.033**	0.063***	0.037**	0.030*	0.057***	0.029*
	(1.62)	(5.46)	(1.73)	(2.46)	(4.63)	(2.68)	(1.79)	(4.07)	(1.94)
CMS x Top HP tercile indicator			0.041***						
			(3.42)						
Hadlock and Pierce (HP)			-0.053						
			(-0.75)						
CMS x Top WW tercile indicator						0.028**			
						(2.26)			
Whited and Wu (WW)						-0.155***			
						(-2.80)			
CMS x No credit rating									0.031***
									(3.50)
No credit rating									0.251***
									(5.78)
Constant	1.743***	0.524***	1.142***	1.753***	0.569***	1.186***	2.022***	0.754***	0.862***
	(18.77)	(10.14)	(16.60)	(19.35)	(14.32)	(33.71)	(17.50)	(37.67)	(22.93)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	38,596	38,607	77,203	29,545	29,556	59,101	22,557	54,916	77,473
R^2	0.173	0.146	0.163	0.174	0.137	0.152	0.147	0.168	0.182

Table 4
Conditioning on Financial Constraints (Continued)

	Panel B: Dependent variable is total net debt issuance								
	Bottom HP tercile	Top HP tercile	Top and bottom HP terciles	Bottom WW tercile	Top WW tercile	Top and bottom HP terciles	With credit rating	Without credit rating	Full sample
CMS	0.071**	0.141***	0.071**	0.086**	0.177***	0.092**	0.092**	0.154***	0.088**
	(2.11)	(4.38)	(2.08)	(2.26)	(5.46)	(2.44)	(2.32)	(4.49)	(2.14)
CMS x Top HP tercile indicator			0.074**						
			(2.14)						
Hadlock and Pierce (HP)			-0.561***						
			(-3.57)						
CMS x Top WW tercile indicator						0.085**			
						(2.39)			
Whited and Wu (WW)						-0.323***			
						(-2.81)			
CMS x No credit rating									0.072*
									(1.97)
No credit rating									0.410**
									(2.46)
Constant	2.329***	-0.672***	1.103***	2.304***	0.034	1.313***	3.419***	0.483***	0.840***
	(12.09)	(-7.41)	(6.79)	(13.28)	(0.48)	(16.03)	(13.12)	(11.50)	(5.26)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	38,590	38,606	77,196	29,539	29,556	59,095	22,579	54,990	77,569
R^2	0.092	0.104	0.101	0.092	0.103	0.097	0.115	0.102	0.113

Table 5
Conditioning on Debt Dependence

This table presents coefficient estimates from regressing corporate investment (Panel A) and net debt issuance (Panel B) on credit market sentiment (measured as in Greenwood and Hanson (2013)) and three measures of debt dependence: private versus public status (in the first three columns), an indicator for whether the firm has above median Hadlock and Pierce (2010) index and above median target leverage (in the middle three columns) and an indicator for whether the firm has above median debt reliance and below median equity reliance for addressing liquidity concerns, as measured by Hoberg and Maksimovic (2015) (in the last three columns). All specifications include firm fixed-effects, firm-level controls (Tobin's Q, Cash flow to assets, Log total assets, Cash to assets, Book leverage, Sales growth, ROA) and macro-level controls (the Leading Economic Index from the Conference Board, the Jurado, Ludvigson, and Ng (2015) index of macro uncertainty, the Baker and Wurgler (2006) sentiment index, and the default spread). The only exception is that Tobin's Q is not available for private firms and so we cannot use it as a control in the first three columns. Standard errors are computed using Driscoll-Kraay (1998) to account for time-series correlation between error terms. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Dependent variable is total corporate investment								
	Public	Private	Public and private	Low DD(HP)	High DD(HP)	High and low DD(HP)	Low DD(HM)	High DD(HM)	High and low DD(HM)
CMS	0.049***	0.118***	0.049***	0.045***	0.064***	0.046***	0.025	0.057***	0.030*
	(3.29)	(3.71)	(3.29)	(3.09)	(3.73)	(3.13)	(1.65)	(3.81)	(1.75)
CMS x Private firm indicator			0.069**						
			(2.61)						
CMS x High DD(HP) indicator						0.020*			
						(1.70)			
CMS x High DD(HM) indicator									0.024**
									(2.28)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	82,997	42,871	125,868	95,678	18,520	114,198	25,320	9,715	35,035
R^2	0.091	0.107	0.098	0.186	0.138	0.183	0.202	0.181	0.198

Table 5
Conditioning on Debt Dependence (Continued)

	Panel B: Dependent variable is total net debt issuance								
	Public	Private	Public and private	Low DD(HP)	High DD(HP)	High and low DD(HP)	Low DD(HM)	High DD(HM)	High and low DD(HM)
CMS	0.154***	0.227***	0.154***	0.099***	0.164***	0.099***	0.011	0.128**	0.018
	(4.29)	(5.17)	(4.29)	(3.62)	(3.70)	(3.51)	(0.39)	(2.86)	(0.63)
CMS x Private firm indicator			0.073***						
			(3.33)						
CMS x High DD(HP) indicator						0.073***			
						(2.93)			
CMS x High DD(HM) indicator									0.115***
									(3.55)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	83,558	50,271	133,829	95,675	18,519	114,194	25,316	9,715	35,031
R^2	0.099	0.143	0.114	0.102	0.104	0.105	0.131	0.172	0.139

Table 6
Long-Term Effects on Corporate Investment

This table presents coefficient estimates from regressing total investment (Panel A), investment in physical capital (Panel B) and investment in intangible capital (Panel C) up to five years in the future, on current credit market sentiment (measured as in Greenwood and Hanson (2013)) and controls. Column headings Year "k" (k=1...5) mean the dependent variable is measured at time T+k, while all independent variables are measured at time T. All specifications include firm fixed-effects, firm-level controls (Tobin's Q, Cash flow to assets, Log total assets, Cash to assets, Book leverage, Sales growth, ROA) and macro-level controls (the Leading Economic Index from the Conference Board, the Jurado, Ludvigson, and Ng (2015) index of macro uncertainty, the Baker and Wurgler (2006) sentiment index, and the default spread). Standard errors are computed using Driscoll-Kraay (1998) to account for time-series correlation between error terms. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Total investment				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.051***	0.021	-0.016	-0.056***	-0.054***
	(3.76)	(1.29)	(-0.95)	(-3.48)	(-3.26)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	115,827	105,882	96,445	88,088	80,640
R^2	0.182	0.104	0.070	0.062	0.058

	Panel B: Investment in physical capital				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.068***	0.022	-0.015	-0.050***	-0.043**
	(4.61)	(1.58)	(-0.95)	(-3.32)	(-2.31)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	115,856	105,909	97,043	88,648	81,189
R^2	0.146	0.095	0.071	0.062	0.059

	Panel C: Investment in intangible capital				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.038**	0.021	-0.014	-0.058***	-0.059***
	(2.59)	(1.06)	(-0.71)	(-2.88)	(-3.62)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	116,025	106,055	96,619	88,241	80,783
R^2	0.121	0.062	0.038	0.033	0.030

Table 7
Long-Term Effects on Debt Issuance

This table presents coefficient estimates from regressing total net debt issuance (Panel A), long-term net debt issuance (Panel B) and short-term net debt issuance (Panel C) up to five years in the future, on current credit market sentiment (measured as in Greenwood and Hanson (2013)) and controls. Column headings Year "k" (k=1...5) mean the dependent variable is measured at time T+k, while all independent variables are measured at time T. Total net debt issuance is the one year change in total assets minus the one year change in book equity, scaled by lagged total assets. Long-term net debt issuance is the change in long term debt ("dltt"+"dlc" in Compustat) scaled by lagged total assets. Short-term net debt issuance is total net debt issuance minus long-term net debt issuance. All specifications include firm fixed-effects, firm-level controls (Tobin's Q, Cash flow to assets, Log total assets, Cash to assets, Book leverage, Sales growth, ROA) and macro-level controls (the Leading Economic Index from the Conference Board, the Jurado, Ludvigson, and Ng (2015) index of macro uncertainty, the Baker and Wurgler (2006) sentiment index, and the default spread). Standard errors are computed using Driscoll-Kraay (1998) to account for time-series correlation between error terms. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Total net debt issuance				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.112***	-0.022	-0.117***	-0.130***	-0.049
	(3.92)	(-0.71)	(-3.55)	(-3.41)	(-1.19)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	115,968	106,587	97,971	89,591	82,110
R^2	0.104	0.063	0.040	0.030	0.024

	Panel B: Long-term net debt issuance				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.221***	0.023	-0.089**	-0.140***	-0.106*
	(5.90)	(0.68)	(-2.04)	(-2.94)	(-1.90)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	115,875	105,926	97,178	88,773	81,319
R^2	0.113	0.062	0.034	0.023	0.019

	Panel C: Short-term net debt issuance				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	-0.008	-0.073*	-0.144***	-0.113***	0.016
	(-0.32)	(-1.77)	(-4.68)	(-2.99)	(0.48)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	115,861	105,913	97,166	88,762	81,309
R^2	0.056	0.035	0.026	0.023	0.018

Table 8
Long-Term Effects on Loan Issuance

This table presents coefficient estimates from regressing new bank loans (Panel A), new loan originations (Panel B) and new refinanced loans (Panel C) up to five years in the future, on current credit market sentiment (measured as in Greenwood and Hanson (2013)) and controls. Column headings Year "k" (k=1...5) mean the dependent variable is measured at time T+k, while all independent variables are measured at time T. Data on bank loans is obtained from Dealscan. Refinanced loans are the Dealscan loans that are flagged as "renewal" or "refinancing" and loan originations are the ones that are not. We obtain our three dependent variables by summing (for each firm, each year) the dollar amounts of new bank loans in each category (all, origination, refinanced) and dividing it by lagged total assets. All specifications include firm fixed-effects, firm-level controls (Tobin's Q, Cash flow to assets, Log total assets, Cash to assets, Book leverage, Sales growth, ROA) and macro-level controls (the Leading Economic Index from the Conference Board, the Jurado, Ludvigson, and Ng (2015) index of macro uncertainty, the Baker and Wurgler (2006) sentiment index and the default spread). Standard errors are computed using Driscoll-Kraay (1998) to account for time-series correlation between error terms. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: All Dealscan loans				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	-0.027	0.003	-0.101	-0.141**	-0.096
	(-0.34)	(0.03)	(-1.52)	(-2.13)	(-1.56)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	66,455	58,544	51,870	46,076	40,940
R^2	0.011	0.005	0.009	0.007	0.006

	Panel B: Only loan originations				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.034	0.022	-0.079	-0.165**	-0.132**
	(0.63)	(0.48)	(-1.05)	(-2.65)	(-2.60)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	66,455	58,544	51,870	46,076	40,940
R^2	0.016	0.013	0.013	0.012	0.009

	Panel C: Loan refinancing				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	-0.083	-0.030	-0.126	-0.118	-0.054
	(-0.73)	(-0.21)	(-1.06)	(-0.95)	(-0.50)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	66,455	58,544	51,870	46,076	40,940
R^2	0.011	0.008	0.009	0.008	0.007

Table 9
Heterogeneity in Long-Term Effects of Credit Market Sentiment on Investment

This table presents coefficient estimates from regressing total investment (measured as in Peters and Taylor (2017)) on credit market sentiment (measured as in Greenwood and Hanson (2013)) and controls. In each panel, we run tests for a different subset of firms based on whether they are deemed financially dependent. Financially dependent firms are firms that have above median Hadlock and Pierce (2010) index and above median target leverage. In Panel A we use only the firms that are deemed financially dependent by this measure, in Panel B we use only the firms that are not financially dependent, and in Panel C we use both sets of firms. All specifications include firm fixed-effects, firm-level controls (Tobin's Q, Cash flow to assets, Log total assets, Cash to assets, Book leverage, Sales growth, ROA) and macro-level controls (the Leading Economic Index from the Conference Board, the Jurado, Ludvigson, and Ng (2015) index of macro uncertainty, the Baker and Wurgler (2006) sentiment index and the default spread). Standard errors are computed using Driscoll-Kraay (1998) to account for time-series correlation between error terms. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Firms with high debt dependence				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.064***	0.020	-0.006	-0.059**	-0.059***
	(3.73)	(1.41)	(-0.35)	(-2.42)	(-2.95)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	18,520	16,358	14,305	12,611	11,229
R^2	0.138	0.056	0.032	0.025	0.030

	Panel B: Firms with low debt dependence				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.045***	0.019	-0.019	-0.054***	-0.052***
	(3.09)	(1.12)	(-1.08)	(-3.39)	(-3.02)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	95,678	88,112	80,349	73,692	67,700
R^2	0.186	0.107	0.073	0.064	0.058

	Panel C: Combined samples				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS x High debt dependence	0.020*	-0.002	0.006	-0.010	-0.010
	(1.70)	(-0.15)	(0.53)	(-0.52)	(-0.78)
CMS	0.046***	0.019	-0.019	-0.056***	-0.053***
	(3.13)	(1.08)	(-1.10)	(-3.51)	(-3.06)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	114,198	104,470	94,654	86,303	78,929
R^2	0.183	0.104	0.070	0.063	0.058

Table 10
Heterogeneity in Long-Term Effects of Credit Market Sentiment on Debt Issuance

This table presents coefficient estimates from regressing total investment (measured as in Peters and Taylor (2017)) on credit market sentiment (measured as in Greenwood and Hanson (2013)) and controls. In each panel, we run tests for a different subset of firms based on whether they are deemed financially dependent. Financially dependent firms are firms that have above median Hadlock and Pierce (2010) index and above median target leverage. In Panel A we use only the firms that are deemed financially dependent by this measure, in Panel B we use only the firms that are not financially dependent, and in Panel C we use both sets of firms. All specifications include firm fixed-effects, firm-level controls (Tobin's Q, Cash flow to assets, Log total assets, Cash to assets, Book leverage, Sales growth, ROA) and macro-level controls (the Leading Economic Index from the Conference Board, the Jurado, Ludvigson, and Ng (2015) index of macro uncertainty, the Baker and Wurgler (2006) sentiment index and the default spread). Standard errors are computed using Driscoll-Kraay (1998) to account for time-series correlation between error terms. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Firms with high debt dependence				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.164***	-0.021	-0.135***	-0.148***	-0.033
	(3.70)	(-0.55)	(-3.52)	(-2.72)	(-0.65)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	18,519	16,387	14,517	12,843	11,449
R^2	0.104	0.049	0.031	0.024	0.022

	Panel B: Firms with low debt dependence				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.099***	-0.020	-0.115***	-0.124***	-0.050
	(3.62)	(-0.70)	(-3.49)	(-3.40)	(-1.21)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	95,675	88,209	81,356	74,753	68,788
R^2	0.102	0.061	0.037	0.029	0.021

	Panel C: Combined samples				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS x High debt dependence	0.073***	0.006	-0.008	0.000	0.030
	(2.93)	(0.19)	(-0.29)	(0.02)	(1.06)
CMS	0.099***	-0.023	-0.118***	-0.129***	-0.054
	(3.51)	(-0.78)	(-3.60)	(-3.46)	(-1.28)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	114,194	104,596	95,873	87,596	80,237
R^2	0.105	0.062	0.039	0.031	0.023

Table 11
Effect on Corporate Investment, Conditional on Over-extrapolation

This table presents coefficient estimates from regressing total investment (measured as in Peters and Taylor (2017)) on credit market sentiment (measured as in Greenwood and Hanson (2013)) and controls. In each panel, we run tests for a different subset of firms. Every fiscal year, each time an analyst consensus forecast is issued (for the current fiscal year EPS), we calculate the difference between that forecast and the consensus forecast (for the same figure) made 12 months prior. We normalize this forecast revision by the stock price two days before the revision, and we then take an average of all the revisions in the current fiscal year. In Panel A, we run tests using only the firms in the top decile with respect to our forecast revision variable, and in Panel B we use only firms in the bottom decile. In Panel C we combine the samples from Panels A and B. All specifications include our main firm-level controls (Tobin's Q, Cash flow to assets, Log total assets, Cash to assets, Book leverage, Sales growth, ROA) and macro-level controls (the Leading Economic Index from the Conference Board, the Jurado, Ludvigson, and Ng (2015) index of macro uncertainty, the Baker and Wurgler (2006) sentiment index and the default spread). Standard errors are computed using Driscoll-Kraay (1998) to account for time-series correlation between error terms. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Firms with highest analyst forecast revisions				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.093**	0.026	-0.019	-0.055	-0.069**
	(2.38)	(0.55)	(-0.65)	(-1.55)	(-2.62)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No	No
N	4,892	4,575	4,231	3,950	3,656
R^2	0.178	0.096	0.052	0.054	0.032

	Panel B: Firms with lowest analyst forecast revisions				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.042**	0.065	-0.022	0.005	-0.037
	(2.07)	(1.65)	(-0.58)	(0.18)	(-1.06)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No	No
N	4,677	4,126	3,649	3,272	2,975
R^2	0.192	0.116	0.062	0.032	0.027

	Panel C: Combined samples				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS x High-revision dummy	0.050	-0.039	0.003	-0.059**	-0.032
	(1.32)	(-0.75)	(0.06)	(-2.36)	(-0.76)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No	No
N	9,569	8,701	7,880	7,222	6,631
R^2	0.216	0.121	0.062	0.047	0.030

Table 12
Effect on Debt Issuance, Conditional on Over-extrapolation

This table presents coefficient estimates from regressing total net debt issuance (change in total assets minus change in book equity, scaled by lagged total assets) on credit market sentiment (measured as in Greenwood and Hanson (2013)) and controls. Every fiscal year, each time an analyst consensus forecast is issued (for the current fiscal year EPS), we calculate the difference between that forecast and the consensus forecast (for the same figure) made 12 months prior. We normalize this forecast revision by the stock price two days before the revision and we then take an average of all the revisions in the current fiscal year. In Panel A, we run tests using only the firms in the top decile with respect to our forecast revision variable, and in Panel B we use only firms in the bottom decile. In Panel C we combine the samples from Panels A and B. All specifications include our main firm-level controls (Tobin's Q, Cash flow to assets, Log total assets, Cash to assets, Book leverage, Sales growth, ROA) and macro-level controls (the Leading Economic Index from the Conference Board, the Jurado, Ludvigson, and Ng (2015) index of macro uncertainty, the Baker and Wurgler (2006) sentiment index and the default spread). Standard errors are computed using Driscoll-Kraay (1998) to account for time-series correlation between error terms. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Firms with highest analyst forecast revisions				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.228***	-0.047	-0.069	-0.205***	-0.131***
	(5.33)	(-0.68)	(-1.31)	(-3.75)	(-3.48)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No	No
N	4,901	4,605	4,318	4,031	3,727
R^2	0.039	0.018	0.007	0.010	0.008

	Panel B: Firms with lowest analyst forecast revisions				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.108**	0.097	-0.100	-0.054	-0.022
	(2.25)	(1.09)	(-1.57)	(-1.08)	(-0.43)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No	No
N	4,681	4,164	3,720	3,346	3,038
R^2	0.082	0.022	0.012	0.012	0.006

	Panel C: Combined samples				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS x High-revision dummy	0.120*	-0.144	0.031	-0.151***	-0.109*
	(1.94)	(-1.47)	(0.45)	(-2.99)	(-1.73)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	No	No
N	9,582	8,769	8,038	7,377	6,765
R^2	0.069	0.025	0.011	0.011	0.007

Table 13
Effect on Forecast Error, Conditional on Over-extrapolation

This table presents coefficient estimates from regressing analyst forecast errors on credit market sentiment (measured as in Greenwood and Hanson (2013)) and controls. Analyst forecast errors are measured as the difference between actual EPS in fiscal year $t+k$ minus the average consensus forecast for this number made in fiscal year t. This difference is normalized by the stock price two days before the first forecast made in year t. Each column corresponds to a different k, from 0 to 4. Every fiscal year, each time an analyst consensus forecast is issued (for the current fiscal year EPS), we calculate the difference between that forecast and the consensus forecast (for the same figure) made 12 months prior. We normalize this forecast revision by the stock price two days before the revision and we then take an average of all the revisions in the current fiscal year. In Panel A, we run tests using only the firms in the top decile with respect to our forecast revision variable, and in Panel B we use only firms in the bottom decile. All specifications include our main firm-level controls (Tobin's Q, Cash flow to assets, Log total assets, Cash to assets, Book leverage, Sales growth, ROA) and macro-level controls (the Leading Economic Index from the Conference Board, the Jurado, Ludvigson, and Ng (2015) index of macro uncertainty, the Baker and Wurgler (2006) sentiment index and the default spread). Standard errors are computed using Driscoll-Kraay (1998) to account for time-series correlation between error terms. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Year 1	Year 2	Year 3	Year 4	Year 5
CMS x Forecast revision	0.001	0.002	0.017	0.007	-0.013*
	(0.19)	(0.33)	(1.50)	(0.92)	(-1.82)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	46,118	42,732	18,671	8,414	5,094
R^2	0.219	0.069	0.034	0.030	0.021

Table 14
Moments

This table presents several empirical moments from our sample ("Empirical moment" column) as well as the theoretical moments for four different models: the model with rational expectations and no financial frictions ("RE model"), the model with rational expectations and financial frictions ("RE+FF model"), the model with diagnostic expectations and no financial frictions ("DE model"), and the model with diagnostic expectations and financial frictions ("DE+FF model"). We report means and standard deviations ("SD") for investment, profitability, leverage, forecast revisions and forecast errors. Because forecast revisions and forecast errors are available at different horizons, the estimates reported are averages for the mean and standard deviation statistics calculated for each horizon. Due to data availability, we use horizons of $t+1$ to $t+4$ for forecast revisions and $t+1$ to $t+5$ for forecast errors.

	Empirical moment	RE model	RE+FF model	DE model	DE+FF model
Mean investment	0.149	0.150	0.150	0.150	0.150
SD Investment	0.236	0.007	0.009	0.011	0.016
Mean profitability	0.123	0.122	0.107	0.122	0.107
SD profitability	0.170	0.010	0.010	0.009	0.008
Mean leverage	0.289		0.330		0.330
SD leverage	0.228		0.003		0.005
Mean forecast revision	-0.013	0.000	0.000	-0.014	-0.012
SD forecast revision	0.050	0.003	0.003	0.005	0.004
Mean forecast error	-0.035	0.000	0.000	-0.036	-0.030
SD forecast error	0.090	0.009	0.009	0.006	0.007

Appendix A: Baseline Model with no Financial Frictions

A.1. The Model

The firm's optimal policy in year t maximizes the expected present value of earnings:

$$\max_{\{I_s, K_{s+1}\}_{s=t}^{\infty}} \mathbb{E}_t \left\{ \sum_{s \geq t}^{\infty} \beta^{s-t} \left[A_s K_s^{\alpha} - I_s - C\left(I_s, K_s\right) K_s \right] \right\}$$

subject to $K_{s+1} = (1-\delta) K_s + I_s$. We assume the commonly used quadratic investment adjustment costs:

$$C\left(I_s, K_s\right) = \frac{\chi}{2} \left(\frac{I_s}{K_s} - \delta \right)^2$$

The Lagrangian is

$$\mathcal{L} = \mathbb{E}_t \left\{ \sum_{s \geq t}^{\infty} \beta^{s-t} \left[A_s K_s^{\alpha} - I_s - C\left(I_s, K_s\right) K_s - q_s \left(K_{s+1} - I_s - (1-\delta) K_s \right) \right] \right\}$$

and the first order conditions w.r. to I_t and K_{t+1} are:

$$\begin{aligned} q_t - 1 &= \chi \left(\frac{I_t}{K_t} - \delta \right) \\ q_t &= \beta \mathbb{E}_t \left[\alpha A_{t+1} K_{t+1}^{\alpha-1} + \chi \frac{I_{t+1}}{K_{t+1}} \left(\frac{I_{t+1}}{K_{t+1}} - \delta \right) - \frac{\chi}{2} \left(\frac{I_{t+1}}{K_{t+1}} - \delta \right)^2 + q_{t+1} (1-\delta) \right] \end{aligned}$$

The FOC w.r. to I implies

$$\frac{I_t}{K_t} = \delta + \frac{q_t - 1}{\chi}$$

Now take the FOC w.r. to K_{t+1}, multiply both sides by K_{t+1}, and obtain:

$$K_{t+1} q_t = \beta \mathbb{E}_t \left[\alpha A_{t+1} K_{t+1}^{\alpha} + \chi I_{t+1} \left(\frac{I_{t+1}}{K_{t+1}} - \delta \right) - \frac{\chi}{2} K_{t+1} \left(\frac{I_{t+1}}{K_{t+1}} - \delta \right)^2 + K_{t+1} q_{t+1} (1-\delta) \right]$$

Now exploit constant returns to scale of investment costs

$$C\left(I_t, K_t\right) K_t = I_t \frac{\partial C}{\partial I_t} + K_t \frac{\partial C}{\partial K_t} = I_t \chi \left(\frac{I_t}{K_t} - \delta \right) - I_t \chi \left(\frac{I_t}{K_t} - \delta \right) + \frac{\chi}{2} K_t \left(\frac{I_t}{K_t} - \delta \right)^2 = \frac{\chi}{2} \left(\frac{I_t}{K_t} - \delta \right)^2 K_t$$

and consider the definition of profits, $\Pi_t = A_t K_t^{\alpha} - C\left(I_t, K_t\right) K_t - I_t$, to obtain

$$K_{t+1} q_t = \beta \mathbb{E}_t \left[\Pi_{t+1} + K_{t+2} q_{t+1} \right]$$

now do forward iteration and impose $\lim_{T \longrightarrow \infty} \beta^T \mathbb{E}_t \left[q_{t+T} K_{t+T+1} \right] = 0$

$$K_{t+1} q_t = \sum_{s \geq t}^{\infty} \beta^{s-t} \mathbb{E}_s \left[\Pi_{s+1} \right] = V_t$$

Therefore we can write

$$q_t = \frac{\sum_{s \geq t}^{\infty} \beta^{s-t} \mathbb{E}_s \left[\Pi_{s+1} \right]}{K_{t+1}}$$

and as a result, substituting back into the FOC for I_t yields the standard investment equation:

$$\frac{I_t}{K_t} = \delta - \frac{1}{\chi} + \frac{\beta}{\chi} \frac{\mathbb{E}\left[\sum_{s \geq t+1}^{\infty} \beta^{s-(t+1)} \Pi_{s+1} \right]}{K_{t+1}}$$

A.2. Steady State

Consider the FOC for K_{t+1}, define $\beta = \frac{1}{1+r}$, and rearrange. Obtain:

$$q_t = \frac{1}{1+r} \mathbb{E}_t \left[\alpha A_{t+1} K_{t+1}^{\alpha-1} + \chi \frac{I_{t+1}}{K_{t+1}} \left(\frac{I_{t+1}}{K_{t+1}} - \delta \right) - \frac{\chi}{2} \left(\frac{I_{t+1}}{K_{t+1}} - \delta \right)^2 + q_{t+1} \left(1 - \delta \right) \right]$$

Now, let's substitute the first order condition for I_t,

$$I_{t+1} = \delta K_{t+1} + \frac{q_{t+1} - 1}{\chi} K_{t+1}$$

in the first order condition for K_{t+1}, and obtain:

$$-q_t + \frac{1}{1+r} \mathbb{E}_t \left[\alpha A_{t+1} K_{t+1}^{\alpha-1} + \chi \left(\delta + \frac{q_{t+1} - 1}{\chi} \right) \left(\frac{q_{t+1} - 1}{\chi} \right) - \frac{\chi}{2} \left(\frac{q_{t+1} - 1}{\chi} \right)^2 + q_{t+1} \left(1 - \delta \right) \right] = 0$$

In the steady state, $q_t = \overline{q}$, $\mathbb{E}_t \left[q_{t+1} \right] - q_t = \Delta \overline{q} = 0$, and $\overline{I} = \delta \overline{K}$, which implies $\overline{q} = 1$. Imposing these conditions on the above equation, we obtain the following steady state values:

$$\begin{aligned} \overline{K} &= \left(\frac{\alpha A_t}{r+\delta} \right)^{\frac{1}{1-\alpha}} \\ \overline{q} &= 1 \\ \overline{I} &= \delta \overline{K} = \delta \left(\frac{\alpha A_t}{r+\delta} \right)^{\frac{1}{1-\alpha}} \end{aligned}$$

Appendix B: Model with Financial Frictions

B.1. The Model

The firm's optimal policy in year t is now:

$$\max_{\{I_s, B_{s+1}, K_{s+1}\}_{s=t}^{\infty}} \mathbb{E}_t \left\{ \sum_{s \geq t}^{\infty} \beta^{s-t} [(1-\tau)[A_s K_s^{\alpha} - C(I_s, K_s) K_s] - I_s + B_{s+1} \right. \\ \left. - [1 + r^B (1-\tau)] B_s - C^D (B_{s+1}, K_{s+1})] \right\} \tag{7}$$

subject to $K_{s+1} = (1-\delta) K_s + I_s$, where:

$$\begin{aligned} C(I_s, K_s) &= \frac{\chi}{2} \left(\frac{I_s}{K_s} - \delta \right)^2 \\ C^D(B_s, K_s) &= \phi_0 e^{-\phi_1 \cdot \left(\frac{\eta K_s}{B_s} - 1 \right)} \end{aligned}$$

The Lagrangian is

$$\mathcal{L} = \mathbb{E}_t \left\{ \sum_{s \geq t}^{\infty} \beta^{s-t} [(1-\tau)[A_s K_s^{\alpha} - C(I_s, K_s) K_s] - I_s + B_{s+1} - [1 + (1-\tau) r^B] B_s \right. \\ \left. - C^D (B_{s+1}, K_{s+1}) - q_s (K_{s+1} - I_s - (1-\delta) K_s)] \right\} \tag{8}$$

and the first order conditions w.r. to I_t, K_{t+1} and B_{t+1} are:

$$q_t - 1 = \chi \left(\frac{I_t}{K_t} - \delta \right) (1-\tau) \tag{9}$$

$$q_t = \beta \mathbb{E}_t \left[\alpha A_{t+1} K_{t+1}^{\alpha-1} (1-\tau) + \chi \frac{I_{t+1}}{K_{t+1}} \left(\frac{I_{t+1}}{K_{t+1}} - \delta \right) (1-\tau) - \frac{\chi}{2} \left(\frac{I_{t+1}}{K_{t+1}} - \delta \right)^2 (1-\tau) \right. \\ \left. + q_{t+1} (1-\delta) \right] + \mathbb{E}_t \left[\phi_1 \phi_0 \frac{\eta}{B_{t+1}} e^{-\phi_1 \cdot \left(\frac{\eta K_{t+1}}{B_{t+1}} - 1 \right)} \right] \tag{10}$$

$$1 = \frac{1}{1+r} \left[1 + (1-\tau) r^B \right] + \mathbb{E}_t \left\{ \phi_1 \phi_0 \frac{\eta K_{t+1}}{B_{t+1}^2} e^{-\phi_1 \cdot \left(\frac{\eta K_{t+1}}{B_{t+1}} - 1 \right)} \right\} \tag{11}$$

B.2. Steady State

In steady state $\overline{B} = \eta \overline{K}$. Furthermore, in equilibrium $r^B = r$. Hence the FOC w.r. to B_{t+1} becomes:

$$\eta \overline{K} \tau r = \phi_1 \phi_0 (1+r)$$

Now use the first order condition for I_t,

$$I_t = \delta K_t + \frac{q_t - 1}{\chi (1-\tau)} K_t$$

and substitute it in the first order condition for K_{t+1}. In the steady state, $q_t = \overline{q}$, and $\mathbb{E}_t\left[q_{t+1}\right] - q_t = \Delta\overline{q} = 0$. Furthermore, in the steady state, $\overline{I} = \delta\overline{K}$, which implies that $\overline{q} = 1$. Moreover, we have $\overline{B} = \eta\overline{K}$. Rearranging terms:

$$\overline{q} = \frac{1}{r+\delta}\left[\alpha A_t \overline{K}^{\alpha-1}\left(1-\tau\right) + \frac{\phi_1\phi_0}{\overline{K}}\left(1+r\right)\right]$$

We obtain the following steady state values:

$$\begin{aligned}
\overline{K} &= \left[\frac{\alpha A_t\left(1-\tau\right)}{r+\delta-\eta\tau r}\right]^{\frac{1}{1-\alpha}} \\
\overline{q} &= 1 \\
\overline{I} &= \delta\overline{K} = \delta\left[\frac{\alpha A_t\left(1-\tau\right)}{r+\delta-\eta\tau r}\right]^{\frac{1}{1-\alpha}} \\
\phi_0 &= \frac{\eta\tau r}{\phi_1\left(1+r\right)}\left[\frac{\alpha A_t\left(1-\tau\right)}{r+\delta-\eta\tau r}\right]^{\frac{1}{1-\alpha}} \\
\overline{B} &= \eta\overline{K} = \eta\left[\frac{\alpha A_t\left(1-\tau\right)}{r+\delta-\eta\tau r}\right]^{\frac{1}{1-\alpha}}
\end{aligned}$$

Appendix C: Forecast Revisions and Forecast Errors

Now let's proceed to compute the k-period ahead forecast of investment (following Lemma 1 in Bordalo et al (2018):

$$\mathbb{E}_t^{\theta}\left(i_{t+k}\right) = \mathbb{E}_t^{\theta}\left[b_0\left(1-\rho\right) + \rho i_{t+k-1} + b_1\rho\left(1+\theta\right)\epsilon_{t+k} - b_1\theta\rho^2\epsilon_{t+k-1}\right]$$

Note that $\mathbb{E}_t^{\theta}\left(\epsilon_{t+k}\right) = 0$ for any $k > 0$ because rational expectations of future shocks are always zero. Thus for $k > 1$, $\mathbb{E}_t^{\theta}\left(i_{t+k}\right)$ becomes

$$\begin{aligned}
\mathbb{E}_t^{\theta}\left(i_{t+k}\right) &= b_0\left(1-\rho\right)\sum_{s=0}^{k-2}\rho^s + \rho^{k-1}\mathbb{E}_t^{\theta}\left(i_{t+1}\right) = b_0\left(1-\rho\right)\sum_{s=0}^{k-1}\rho^s + \rho^k i_t \\
&= b_0\left(1-\rho^k\right) + \rho^k i_t
\end{aligned}$$

Therefore,

$$i_{t+1} - \mathbb{E}_t^{\theta}\left(i_{t+1}\right) = b_1\left[\mathbb{E}_{t+1}^{\theta}\left(i_{t+2}\right) - \mathbb{E}_t^{\theta}\left(\mathbb{E}_{t+1}^{\theta}\left(i_{t+2}\right)\right)\right]$$

Now note that $\mathbb{E}_{t+1}^{\theta}\left(i_{t+2}\right) = \mathbb{E}_{t+1}\left(i_{t+2}\right) + \theta\rho\epsilon_{t+1}$ and $\mathbb{E}_t^{\theta}\left[\mathbb{E}_{t+1}^{\theta}\left(i_{t+2}\right)\right] = \mathbb{E}_t\left(i_{t+2}\right) + \theta\rho^2\epsilon_t$. Taking the expectation of the difference, we find that

$$\mathbb{E}_t\left[i_{t+1} - \mathbb{E}_t^{\theta}\left(i_{t+1}\right)\right] = -b_1\theta\rho^2\epsilon_t$$

Following similar steps, we can derive the forecast error,

$$\mathbb{E}_t\left[\mathbb{E}_{t+k}^{\theta}\left(i_{t+T}\right) - \mathbb{E}_t^{\theta}\left(i_{t+T}\right)\right] = -b_1\theta\rho^{T+1}\epsilon_t$$

Appendix D: Tables

Table D.1
Controlling for Firm-Level Credit Worthiness

This table presents coefficient estimates from regressing total investment (measured as in Peters and Taylor (2017)) on credit market sentiment (measured as in Greenwood and Hanson (2013)) and various measures of credit worthiness (each column corresponds to a different measure). All specifications include firm fixed-effects, firm-level controls (Tobin's Q, Cash flow to assets, Log total assets, Cash to assets, Book leverage, Sales growth, ROA) and macro-level controls (the Leading Economic Index from the Conference Board, the Jurado, Ludvigson, and Ng (2015) index of macro uncertainty, the Baker and Wurgler (2006) sentiment index and the default spread). Standard errors are clustered at the firm and year level. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
CMS	0.051***	0.044**	0.050***	0.053***
	(3.76)	(2.69)	(3.94)	(4.12)
Credit quality	-0.101***			
	(-6.34)			
Campbell, Hilsher and Szilagyi (2008) index		-0.156***		
		(-10.97)		
Ohlson (1980) O score			0.001	
			(0.05)	
Altman (1968) Z score				-0.096***
				(-6.20)
Constant	1.071***	0.991***	0.935***	0.929***
	(62.82)	(52.30)	(63.96)	(61.54)
Firm-level controls	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
N	115,827	105,708	131,242	131,352
R^2	0.182	0.180	0.172	0.173

Table D.2
Long-Term Effects on Sources of External Financing Using All Firms

This table presents coefficient estimates from regressing net debt issuance (Panel A), net equity repurchases (Panel B) and net external financing (Panel C) up to five years in the future, on current credit market sentiment (measured as in Greenwood and Hanson (2013)) and controls. Column headings Year "k" (k=1...5) mean the dependent variable is measured at time T+k, while all independent variables are measured at time T. Following Ma (2018), net debt issuance is long-term debt issuance (DLTIS) minus long-term debt reduction (DLTR) divided by total assets. Net equity repurchases are calculated as purchase of common and preferred stock (PRSTKC) minus sale of common and preferred stock (SSTK), divided by total assets. Net external financing is net debt issuance minus net equity repurchases. All specifications include firm fixed-effects, firm-level controls (Tobin's Q, Cash flow to assets, Log total assets, Cash to assets, Book leverage, Sales growth, ROA) and macro-level controls (the Leading Economic Index from the Conference Board, the Jurado, Ludvigson, and Ng (2015) index of macro uncertainty, the Baker and Wurgler (2006) sentiment index and the default spread). Standard errors are clustered at the firm and year level. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Net Debt Issuance				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.487***	0.127	-0.091	-0.334***	-0.361***
	(5.40)	(1.34)	(-1.01)	(-2.94)	(-2.93)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	105,006	97,601	90,467	83,490	77,193
R^2	0.076	0.048	0.026	0.017	0.014

	Panel B: Net Equity Repurchases				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.263***	0.119	0.106	-0.039	-0.170*
	(2.87)	(1.07)	(1.25)	(-0.68)	(-1.79)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	103,975	96,739	89,806	83,016	76,858
R^2	0.091	0.046	0.032	0.025	0.021

	Panel C: Net External Financing				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.254**	0.019	-0.202*	-0.287***	-0.165
	(2.24)	(0.17)	(-1.94)	(-2.73)	(-1.57)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	98,265	91,436	84,872	78,418	72,548
R^2	0.085	0.051	0.039	0.032	0.027

Table D.3
Long-Term Effects on Sources of External Financing Using Firms In Top Size Decile

This table presents the same tests as in Table D.2 restricted to the subsample of firms in the top size decile each year, where size is measured as the firm's book value of debt (total assets minus book equity) plus the firm's market capitalization (price times number of shares outstanding) at the end of the fiscal year. Standard errors are clustered at the firm and year level. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Net Debt Issuance				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.298***	0.295***	0.262***	-0.025	-0.391***
	(2.92)	(2.92)	(3.02)	(-0.23)	(-3.29)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	13,446	13,080	12,672	12,145	11,634
R^2	0.058	0.040	0.026	0.014	0.011

	Panel B: Net Equity Repurchases				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.322***	0.180*	-0.108	-0.401***	-0.520***
	(4.05)	(2.01)	(-1.07)	(-3.91)	(-4.87)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	13,266	12,916	12,525	12,001	11,504
R^2	0.126	0.090	0.071	0.071	0.070

	Panel C: Net External Financing				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	-0.032	0.137	0.364***	0.411***	0.183
	(-0.28)	(1.13)	(3.20)	(3.09)	(1.42)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	12,443	12,122	11,760	11,273	10,805
R^2	0.072	0.050	0.048	0.040	0.027

Table D.4
Long-Term Effects on Sources of External Financing Using Firms In Bottom Nine Size Deciles

This table presents the same tests as in Table D.2 restricted to the subsample of firms in the bottom nine size deciles each year, where size is measured as the firm's book value of debt (total assets minus book equity) plus the firm's market capitalization (price times number of shares outstanding) at the end of the fiscal year. Standard errors are clustered at the firm and year level. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: Net Debt Issuance				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.526***	0.107	-0.140	-0.369***	-0.335**
	(5.70)	(1.07)	(-1.41)	(-2.86)	(-2.49)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	91,555	84,517	77,792	71,343	65,557
R^2	0.082	0.050	0.027	0.017	0.014

	Panel B: Net Equity Repurchases				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.265**	0.120	0.149	0.032	-0.110
	(2.66)	(0.95)	(1.64)	(0.53)	(-1.11)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	90,704	83,819	77,278	71,013	65,352
R^2	0.092	0.042	0.027	0.020	0.015

	Panel C: Net External Financing				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.299**	0.002	-0.291**	-0.393***	-0.203
	(2.31)	(0.01)	(-2.47)	(-2.96)	(-1.64)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	85,817	79,310	73,109	67,143	61,741
R^2	0.088	0.049	0.036	0.028	0.024

Table D.5
Long-Term Effects on Investment, Conditioning on Firm Size

This table presents coefficient estimates from regressing total investments (as in Peters and Taylor 2017) up to five years in the future, on current credit market sentiment (measured as in Greenwood and Hanson (2013)) and controls. Panel A runs these regressions using all firms, Panel B uses only firms in the top size decile and Panel C uses the firms in the bottom nine size deciles. Size is measured as the firm's book value of debt (total assets minus book equity) plus the firm's market capitalization (price times number of shares outstanding) at the end of the fiscal year. Column headings Year "k" (k=1...5) mean the dependent variable is measured at time T+k, while all independent variables are measured at time T. All specifications include firm fixed-effects, firm-level controls (Tobin's Q, Cash flow to assets, Log total assets, Cash to assets, Book leverage, Sales growth, ROA) and macro-level controls (the Leading Economic Index from the Conference Board, the Jurado, Ludvigson, and Ng (2015) index of macro uncertainty, the Baker and Wurgler (2006) sentiment index and the default spread). Standard errors are clustered at the firm and year level. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Panel A: All Firms				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.051***	0.021	-0.016	-0.056***	-0.054***
	(3.76)	(1.29)	(-0.95)	(-3.48)	(-3.26)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	115,827	105,882	96,445	88,088	80,640
R^2	0.182	0.104	0.070	0.062	0.058
	Panel B: Firms in Top Size Decile				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.023	0.017	0.003	-0.033	-0.039**
	(1.23)	(0.96)	(0.14)	(-1.58)	(-2.18)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	15,007	14,414	13,692	13,001	12,348
R^2	0.171	0.116	0.085	0.070	0.057
	Panel C: Firms in Bottom Nine Size Deciles				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.058***	0.025	-0.016	-0.057***	-0.054***
	(4.18)	(1.45)	(-0.92)	(-3.54)	(-3.18)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	100,813	91,462	82,749	75,085	68,290
R^2	0.179	0.098	0.063	0.053	0.049

Table D.6
Long-Term Effects on Corporate Investment by Sector

This table presents coefficient estimates from regressing total investment (measured as in Peters and Taylor (2017)) up to five years in the future, on current credit market sentiment (measured as in Greenwood and Hanson (2013)) and controls. Each panel uses data from a separate sector in the Fama and French (1997) 12 industry classification. Utilities (Sector 8) and financials (Sector 11) are excluded. Column headings Year "k" (k=1...5) mean the dependent variable is measured at time T+k, while all independent variables are measured at time T. All specifications include firm fixed-effects, firm-level controls (Tobin's Q, Cash flow to assets, Log total assets, Cash to assets, Book leverage, Sales growth, ROA) and macro-level controls (the Leading Economic Index from the Conference Board, the Jurado, Ludvigson, and Ng (2015) index of macro uncertainty, the Baker and Wurgler (2006) sentiment index and the default spread). Standard errors are clustered at the firm and year level. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Sector 1: Consumer NonDurables – Food, Tobacco, Textiles, Apparel, Leather, Toys				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.043***	0.029**	0.010	-0.006	0.007
	(2.78)	(2.16)	(0.69)	(-0.50)	(0.64)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	10,801	10,009	9,253	8,542	7,891
R^2	0.132	0.086	0.062	0.049	0.045
	Sector 2: Consumer Durables – Cars, TV's, Furniture, Household Appliances				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.063***	-0.002	-0.049**	-0.058***	-0.017
	(3.53)	(-0.09)	(-2.60)	(-3.19)	(-0.66)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	4,734	4,379	4,041	3,738	3,455
R^2	0.167	0.102	0.060	0.050	0.045
	Sector 3: Manufacturing – Machinery, Trucks, Planes, Off Furn, Paper, Com Printing				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.039**	0.020	-0.018	-0.052***	-0.039*
	(2.48)	(1.29)	(-0.98)	(-2.77)	(-1.98)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	21,616	20,179	18,723	17,353	16,098
R^2	0.145	0.086	0.056	0.049	0.044
	Sector 4: Oil, Gas, and Coal Extraction and Products				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.016	-0.007	-0.016	-0.133**	-0.141**
	(0.41)	(-0.14)	(-0.25)	(-2.19)	(-2.57)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	6,274	5,669	5,077	4,585	4,156
R^2	0.188	0.100	0.075	0.070	0.060

Table D.6
Long-Term Effects on Corporate Investment by Sector (Continued)

	Sector 5: Chemicals and Allied Products				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.063***	0.018	-0.016	-0.050***	-0.044**
	(3.43)	(0.94)	(-0.90)	(-2.96)	(-2.51)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	4,286	4,043	3,776	3,537	3,318
R^2	0.140	0.081	0.062	0.049	0.035
	Sector 6: Business Equipment – Computers, Software, and Electronic Equipment				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.066***	0.062*	0.012	-0.059**	-0.069***
	(3.62)	(1.72)	(0.36)	(-2.04)	(-3.46)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	20,294	18,379	16,590	15,050	13,691
R^2	0.249	0.137	0.096	0.085	0.078
	Sector 7: Telephone and Television Transmission				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.068*	0.084	0.029	-0.065*	-0.073
	(1.93)	(1.38)	(0.57)	(-1.71)	(-1.55)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	3,175	2,826	2,512	2,253	2,024
R^2	0.204	0.097	0.057	0.058	0.062
	Sector 9: Wholesale, Retail, and Some Services (Laundries, Repair Shops)				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.055***	0.006	-0.037*	-0.050***	-0.037**
	(3.48)	(0.38)	(-1.94)	(-2.93)	(-2.37)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	16,520	15,036	13,669	12,449	11,371
R^2	0.227	0.162	0.109	0.098	0.097
	Sector 10: Healthcare, Medical Equipment, and Drugs				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.002	-0.016	-0.014	-0.037	-0.065**
	(0.11)	(-0.77)	(-0.66)	(-1.56)	(-2.35)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	10,355	9,300	8,327	7,512	6,791
R^2	0.181	0.106	0.072	0.064	0.060
	Sector 12: Other – Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.066***	0.008	-0.035*	-0.067***	-0.078***
	(3.40)	(0.42)	(-1.76)	(-3.22)	(-3.41)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	17,772	16,062	14,477	13,069	11,845
R^2	0.174	0.095	0.061	0.055	0.057

Table D.7
Long-Term Effects on Debt Issuance by Sector

This table presents coefficient estimates from regressing total net debt issuance (change in total assets minus change in book equity, scaled by lagged total assets) up to five years in the future, on current credit market sentiment (measured as in Greenwood and Hanson (2013)) and controls. Each panel uses data from a separate sector in the Fama and French (1997) 12 industry classification. Utilities (Sector 8) and financials (Sector 11) are excluded. Column headings Year "k" (k=1...5) mean the dependent variable is measured at time T+k, while all independent variables are measured at time T. All specifications include firm fixed-effects, firm-level controls (Tobin's Q, Cash flow to assets, Log total assets, Cash to assets, Book leverage, Sales growth, ROA) and macro-level controls (the Leading Economic Index from the Conference Board, the Jurado, Ludvigson, and Ng (2015) index of macro uncertainty, the Baker and Wurgler (2006) sentiment index and the default spread). Standard errors are clustered at the firm and year level. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Sector 1: Consumer NonDurables – Food, Tobacco, Textiles, Apparel, Leather, Toys				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.087***	0.005	-0.050	-0.034	0.035
	(2.86)	(0.20)	(-1.55)	(-0.82)	(0.87)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	10,807	10,042	9,334	8,628	7,971
R^2	0.107	0.069	0.038	0.028	0.021
	Sector 2: Consumer Durables – Cars, TV's, Furniture, Household Appliances				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.174***	-0.085*	-0.164***	-0.047	0.060
	(2.84)	(-1.74)	(-2.96)	(-0.79)	(0.77)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	4,737	4,401	4,090	3,783	3,500
R^2	0.106	0.057	0.032	0.032	0.029
	Sector 3: Manufacturing – Machinery, Trucks, Planes, Off Furn, Paper, Com Printing				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.070*	-0.025	-0.109**	-0.120**	0.009
	(1.78)	(-0.69)	(-2.37)	(-2.48)	(0.17)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	21,637	20,257	18,920	17,562	16,299
R^2	0.096	0.067	0.035	0.026	0.018
	Sector 4: Oil, Gas, and Coal Extraction and Products				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.073	-0.022	-0.139	-0.263***	-0.173**
	(1.01)	(-0.27)	(-1.46)	(-3.11)	(-2.21)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	6,277	5,703	5,191	4,694	4,263
R^2	0.121	0.067	0.053	0.048	0.039

Table D.7
Long-Term Effects on Debt Issuance by Sector (Continued)

	Sector 5: Chemicals and Allied Products				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.084	-0.013	-0.082	-0.158***	-0.114**
	(1.67)	(-0.31)	(-1.50)	(-3.38)	(-2.16)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	4,288	4,061	3,836	3,599	3,382
R^2	0.075	0.050	0.028	0.026	0.015

	Sector 6: Business Equipment – Computers, Software, and Electronic Equipment				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.098***	0.013	-0.119**	-0.153***	-0.089**
	(3.53)	(0.27)	(-2.57)	(-4.19)	(-2.44)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	20,324	18,529	16,879	15,324	13,956
R^2	0.110	0.065	0.045	0.029	0.025

	Sector 7: Telephone and Television Transmission				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.271***	0.135	0.006	-0.162**	-0.116
	(3.12)	(1.60)	(0.09)	(-2.11)	(-1.35)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	3,180	2,864	2,569	2,313	2,082
R^2	0.125	0.072	0.048	0.050	0.045

	Sector 9: Wholesale, Retail, and Some Services (Laundries, Repair Shops)				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.131***	-0.039	-0.153***	-0.103**	-0.024
	(3.77)	(-1.02)	(-3.64)	(-2.27)	(-0.50)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	16,542	15,111	13,810	12,579	11,497
R^2	0.123	0.075	0.048	0.040	0.034

	Sector 10: Healthcare, Medical Equipment, and Drugs				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.043	-0.037	-0.098*	-0.119**	-0.102**
	(1.04)	(-1.08)	(-1.84)	(-2.66)	(-2.52)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	10,370	9,414	8,552	7,718	6,992
R^2	0.089	0.051	0.037	0.027	0.027

	Sector 12: Other – Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.177***	-0.057	-0.137***	-0.175***	-0.091**
	(4.73)	(-1.33)	(-3.13)	(-3.80)	(-2.07)
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
N	17,806	16,205	14,790	13,391	12,168
R^2	0.118	0.073	0.052	0.043	0.035