Credit Cycles 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.

Keywords: Credit-market sentiment, credit booms, issuer quality, under-investment, over-investment

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Huseyin Gulen, hgulen@purdue.edu, Purdue University, 403 West State Street, West Lafayette, IN 47907.
Mihai Ion, mihaiion@email.arizona.edu, University of Arizona, 1130 E Helen St, Tucson AZ 85721.
Stefano Rossi, stefano.rossi@unibocconi.it, Generali Chair in Insurance and Risk Management, Bocconi University, IGIER and Baffi-Carefin, Via Roentgen 1, Milano 20136, Italy.

1. Introduction

The credit boom of 2006-2007 and the subsequent financial crisis and Great Recession have reignited interest in understanding the connection between financial markets and the real economy (e.g., Reinhart and Rogoff 2009, Borio and Lowe 2002, Schularick and Taylor 2012). López-Salido, Stein, and Zakrajšek (2017) show that high credit market sentiment in year t is associated with a decline in aggregate economic activity in years $t + 2$ and $t + 3$. But what are the transmission mechanisms of credit market instability to the real economy? Recent literature has focused on household borrowing (e.g., Mian, Sufi, and Verner 2017) and intermediaries' balance sheets (e.g., Baron and Xiong 2017, Fahlenbrach, Prilmeier, and Stulz 2018). In this paper, we focus on a different transmission mechanism, namely, firms' balance sheets, and study how credit market shocks affect corporate investment.

In principle, credit market instability does not have to 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.

On the other hand, financial market instability could affect corporate investment through two very different channels. According to the financial frictions literature (e.g., Bernanke and Gertler 1989, Kiyotaki and Moore 1997), borrowers and lenders are fully rational but subject to constraints on the availability of credit for investment activities (e.g., collateral). Accordingly, credit expansions can help constrained borrowers relax their constraints and invest more. Financial frictions such as credit and collateral constraints can thus amplify and propagate the effect of exogenous shocks to generate aggregate fluctuations, which are further amplified in the presence of firm heterogeneity and other frictions.[1]

Recent work in behavioral finance, drawing on classic accounts of financial crises such as Minsky (1977, 1986) and Kindleberger (1978), posits that investor sentiment features cyclical components, which in turn drives predictable reversals in economic activity (Greenwood and Hanson 2013,

[1] We discuss this literature in more detail in Section 5.

López-Salido, Stein, and Zakrajšek 2017). This approach emphasizes that, rather than a sequence of idiosyncratic unexpected shocks propagating through financial frictions, financial market instability affects the real economy exclusively through (biased) expectations (Bordalo, Gennaioli, and Shleifer 2018). When designing investment plans, firms over-extrapolate past shocks to fundamentals, so that when fundamentals turn out worse than expected, firms suddenly revise their expectations downward, triggering predictable long-term reversals in investment.

In this paper, we attempt to shed light on these issues by examining firm-level responses to credit cycles using comprehensive panel data on investment and financing activities of U.S. public and private firms over 1963-2016. Rather than discussing the financial frictions and the behavioral finance literatures separately, we take an integrated view. Indeed, we take as a starting point both the existence of predictable mean reversion in credit market conditions and the existence of financial frictions, while at the same time explicitly allowing for firm heterogeneity. Our objective is to present detailed empirical evidence on the—potentially heterogeneous—response of corporate investment and financing activities by U.S. firms to predictable mean reversion in credit market conditions, with a view to inform both economic theory and policy.

More specifically, we start with the aggregate measure of issuer quality of corporate debt, 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). López-Salido, Stein, and Zakrajšek (2017) further show that the same measure of issuer quality also negatively predicts subsequent aggregate GDP growth. 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 investment 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 4.8% increase in total investment the following year (relative to its mean), which represents the weighted average of a 6.4% increase in investment in physical capital and a 3.5% increase in investment in intangible capital.

We demonstrate that the strong effect of issuer quality 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 cross-sectional and 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. Therefore, we demonstrate that the strong effect of issuer quality on corporate investment is not due to time-invariant firm-level heterogeneity, or to time-varying firm-level default risk, or other firm-level proxies for investment opportunities and balance sheet strength.

Next, we explicitly allow for firm heterogeneity. The financial frictions literature, as well as the model in Stein (1996), imply that buoyant credit market conditions will increase investment by debt-dependent 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. Under standard arguments in corporate finance, firms depend on external financing if they have strong investment opportunities but face some financing constraint such that their access to capital markets is not frictionless.[2] Because among external sources of funds debt is generally less costly than equity, standard pecking order theory (e.g., Myers 1984) implies that the general notion of dependence on external financing often coincides with a dependence on external *debt* financing. Accordingly, rather than developing our own measure, we rely 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.[3]

Our results are very strong and consistent across all our proxies for debt dependence and

[2]Typical examples of financially constrained firms include small and young firms with low cash balances and cash flows, which have possibly some debt outstanding but not too much, and have strong investment opportunities.

[3]One concern with these measures is that to some extent they might capture a generic dependence on external financing (both external debt and equity) rather than exclusively a dependence on debt. To address this concern, we use two additional variables to further rule out that our results are driven by a dependence on equity financing. The first is an indicator variable for privately listed firms. These firms are small and young, and, by definition, have no access to public equity markets. The second is the absence of R&D investment activities. Firms without R&D investment activities are less likely to suffer from debt overhang (Myers 1977) and are thus more likely to depend on debt to finance their marginal investment activities. These strategies are well established in large sample empirical work (e.g., see Polk and Sapienza 2009) and should therefore assuage concerns of data mining that would arise, for example, should we attempt to construct our own preferred measure.

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 such effect is 50% to 100% larger among debt dependent firms.[4]

Next, we examine the long-run effects of credit market sentiment on corporate investment and debt issuance by estimating the impulse response function 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, consistent with the effects of credit market sentiment on firms' balance sheets to go through primarily via investment in tangible and intangible capital rather than through capital structure rebalancing.[5]

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. Our main result is that credit market cycles beget corporate investment cycles. In the short term (one year after the credit market boom), the firms' corporate investment increases, particularly for firms that are financially constrained. In the longer term, credit dries out (three and four years after the credit

[4]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 that our results are strong across the board and not limited to the types of firms traditionally thought of as prone to empire-building or overconfident investment behavior.

[5]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.

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) across the board for all types of firms and almost all sectors of the economy. We discuss the policy implications of our findings in the conclusions.

In the final part of the paper, we explore the mechanism driving our results, and we attempt to establish where these cycles come from. In particular, our results on the long-term reversals in investment are difficult to rationalize purely within extant theories relying on rational expectations and financial frictions. We show that credit cycles and investment cycles are tightly linked to errors in expectations. In this respect, we first establish that in the aggregate, credit cycles are tightly linked to analysts' expectations of future fundamentals. Specifically, we show that the credit market sentiment measure of Greenwood and Hanson (2013) strongly correlates positively with measure of contemporaneous analysts' consensus earnings forecast revisions and with measures of excess analyst optimism. 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 $t+4$. These findings point to systematic over-excitement by analysts, who over-extrapolate fundamentals in the future and then are systematically disappointed.

We then explore this over-extrapolation channel in the cross-section. 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 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 $t+5$ after a credit market boom in year t relative to firms in the bottom decile of analyst forecast revisions. We find very 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. Therefore, our results are consistent with a framework in which predictable cycles in credit markets translate into predictable cycles in corporate investment activity, which occur through the revision of biased expectations and the subsequent expectation errors. We discuss the implications of our findings for economic theory in the conclusion.

The paper proceeds as follows. Section 2 discusses the data and methodology. Section 3 presents the baseline results of credit market sentiment on corporate investment and debt issuance in the short run. Section 4 presents the evidence on the long term effects of credit market sentiment on corporate investment and financing. Section 5 discusses in more detail the relevant theories of macroeconomics and finance and analyses them within the context of the neoclassical Q-theory of investment. Section 6 presents further empirical tests designed to explore the economic mechanism in more detail. Section 7 concludes.

2. Data and Methodology

2.1. Firm-level data

We study a large, unbalanced panel of Compustat firms at annual frequency that covers 1963 through 2016. The panel excludes financial firms (i.e., firms with a one-digit SIC of six), utilities (i.e., firms with two-digit SIC 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. 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 its values over the past year. Table 1 presents summary statistics of firm-level variables. We have over 120,000 firm-year observations and a median number of 2,458 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, 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 equivalently 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

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 5%), and the Baker and Wurgler investor sentiment index (p-value of 8%). 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.

2.4. 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 $k = 2, 3, 4, 5$. In all our specifications, we cluster standard errors at the firm and year level.

3. Credit Booms and Corporate Investment

3.1. Baseline results

In this section we present our 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 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 $t + 1$.[6] 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

[6] 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.

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 affect 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, begetting 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.[7] Higher firm-level default probability is negatively associated with subsequent investment. Our results on the effect of credit market sentiment on corporate investment are unaffected, and their economic magnitude, if anything, is larger than in column 2. In economic terms, in our strictest specification (column 3), a one standard deviation increase in credit market sentiment relative to its mean is associated with a 4.8% 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 6.4% increase in

[7] We show in Table C1 in the Appendix that we obtain very 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.

investment in tangible capital (column 6), and with a 3.5% 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.

3.2. 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. One challenge in interpreting our results in line with a debt-financing channel is that these firms in our data, 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.

Specifically, we use two empirical strategies for isolating a debt-financing channel. First, we examine a sample of private firms obtained from Capital IQ.[8] Private firms tend to be smaller and younger than their public counterparts and, by definition, have no access to external public equity markets. Therefore, it is plausible that private firms finance their marginal investment opportunity 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

[8]Capital IQ provides data on firms that file Form 10-K or Form S-1. According to the SEC, firms have to file Form 10-K if they have 500 or more shareholders and they have total assets of at least $10 million. In addition, firms with public debt have to 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).

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.

Second, we note that theory (e.g., Myers 1977) predicts that firms whose market values reflect disproportionately growth options, such as R&D expenditures, may suffer from debt overhang and are thus likely to depend on public equity markets to finance their marginal investment (see also Polk and Sapienza 2009). Therefore, we introduce an indicator variable for firms with no R&D expenditures. Firms without R&D investment activities are less likely to suffer from debt overhang and are thus more likely to depend on debt to finance their marginal investment activities. The advantage of this latter strategy is that we can adjust for the same large set of confounding firm-level characteristics as in our main tests. The disadvantage is that it still isolates a set of firms that are publicly listed, so in principle equity market sentiment may still play a role, although theory suggests that such a role should be rather limited.

Table 4 presents the results. The dependent variable in Panel A is total corporate investment (Peters and Taylor 2017), and in Panel B it is total net debt issuance (change in total assets minus change in book equity, 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 whether the firm does any R&D in the last three columns. We present specifications using interactions of credit market sentiment with debt dependence (columns 1 and 4) as well as specifications run on separate samples of firms split on debt dependence (columns 2 and 3 for public/private splits and columns 5 and 6 for R&D splits.)

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 3 suggests that a one standard deviation increase in credit market sentiment is associated with a 21.7% increase in investment, relative to the mean, for private firms. This effect is 3.4 times larger than for public firms (column 2). The last three columns in Panel A show that, among public firms, the effect of credit market sentiment on investment is larger for firms without R&D expenditures, yet it is again positive and significant for both. Panel B presents similar results for total net-debt issuance. Overall, the results are consistent with credit market sentiment affecting corporate investment through a debt-dependence channel.

3.3. Credit booms and financial frictions

In this section, we examine the hypothesis from the financial frictions literature that the marginal effect of credit market sentiment should be larger for firms that are more financially constrained. We use four proxies for financial constraints, building on the seminal work of Kaplan and Zingales (1997). In particular, we use the indices of financial constraints recently developed by Hadlock and Pierce (2010) and by Whited and Wu (2006), which have become popular in the more recent literature.[9] 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 in general 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 5 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 of our 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 report both results using an interaction between credit market sentiment and each proxy (columns 4, 6 and 9) as well as results using separate subsamples based on median splits 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, consistent with our hypothesis. 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, particularly for the Hadlock and Pierce (2010) index and the Whited and Wu (2006) index. This is also consistent with our hypothesis.

[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).

4. Long-Term Effects

In this section we examine long term effects. In sub-section 4.1 we examine long-term effects of credit market sentiment on investment and financing, and in sub-section 4.2 we examine cross-sectional heterogeneity in these long-term effects.

4.1. 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.[10] 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 $t+5$ a 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 4.8% increase in investment in year $t+1$, with a 6% decrease in investment in year $t+4$ and with a 5.8% decrease in investment in year $t+5$.

[10] A more general formulation of Jordá's (2005) local projection impulse response function includes also 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.

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 boom in year $t + 1$ is about 50% larger for investment in physical capital; but the economic magnitude of the reversals $t + 4$ and $t + 5$ is much 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 relying 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 comes with 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 comes with an 11% increase in total net debt issuance (re. 11% 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 (7% decline versus 5% decline); in year $t + 4$ and $t + 5$ the decline is larger in long-term debt issuance (7.7% and 5.5% decline, respectively) relative to the decline in short-term net debt issuance (5.3% 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 (Chodorow-Reich 2014). We merge Dealscan data on syndicated lending to Compustat data using the concordance first developed in Chava and Roberts (2008) and updated on Michael Roberts' website.[11] Our final sample contains 63,485 firm-year observations. Panel A examines all syndicated loans, be they 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 14% and 13%, respectively, which translates into a 14% decline in total syndicated loans in year $t+4$.

We also explore the idea that part of the proceeds raised by issuing debt in response to credit market sentiment might be used to repurchase shares (Ma 2018). Tables C2, C3, and C4 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 C2), only firms in the top size decile (Table C3) and only firms in the bottom nine size deciles (Table C4). 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 C3 and Panel C in Table C4). 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 Table C5 in the Appendix, 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 size 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), but 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.

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

4.2. 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 in the economy, as classified by Fama and French (1997).[12] Table C6 in the Appendix shows that the positive effects of a credit market shock in year t on investment in year $t+1$ occurs in 7 out of the 10 sectors (exceptions are the oil, gas, and coal sector, the healthcare, medical equipment, and drugs sector, and the telephone and television transmission sector, although in the latter sector the effect is sizable and low sample size likely drives low statistical power). The largest effects are in the consumer durables sector and in the business equipment 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 the non-durables one (food, tobacco, etc.). Interestingly, the consumer durables and the wholesale retail sectors lead the way, in that in these sectors the reversal begins already in year $t+3$. Table C7 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 various proxies of financial constraints and financial frictions. Table 9 presents the results. Panels A1 and A2 of Table 9 report results on corporate investment, and Panels B1 and B2 of Table 9 report results on total net debt issuance. Table 9 shows that the reversals in investment and in total net debt issuance documented above occur across the board, irrespective of financial frictions and financial constraints. 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.

5. 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

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

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, reversal effects are very strong across the board and not just limited to specific subsets of firms or industries. Figure 2 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 note immediately 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 5.1 discusses theories of rational expectations and financial frictions; sub-section 5.2 discusses behavioral theories based on biased expectations; and sub-section 5.3 formalizes the preceding discussions in the context of the neoclassical Q-theory framework.

5.1. 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.[13]

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 takes time to rebuild. Second, shocks are directly amplified in the presence of leverage. Bernanke and Gertler (1989) and Carlstrom and Fuerst (1997) provide quantifications of these effects 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

[13] 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.

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, leading to an increase (re. decrease) in investment and output, which further increases (re. decreases) these agents' net worth.[14] Together, these insights show that even relatively small shocks can have potentially large effects on the macroeconomy.[15]

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 therefore future transmissions of the shocks.[16]

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, but after an unusually large shock firms can no longer adjust payouts and need to deleverage, i.e., sell capital to cut down their exposures.[17] Similarly, Bianchi (2011) and Mendoza (2010) study international macro-finance models based on occasionally binding collateral constraints and externalities of individual borrowing decisions on 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.[18]

[14]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.

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

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

[17]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.

[18]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).

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 $t+1$; and they explain why this effect should be stronger for debt-dependent firms, as we document in Table 5. These models have difficulty in rationalizing in a parsimonious way why aggregate shocks at time t do not just eventually die out, but generate instead a large and predictable reversal in corporate borrowing and investment in years $t+3$, $t+4$, and $t+5$. 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. These explanations have 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, as 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).

Furthermore, 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 5.3 below. This prediction is at odds with our findings in Table 9, where we find significant reversals across the board, both in high financial constraints and low financial constraints firms.

5.2. Biased expectations

A recent set of theories emphasize 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 hard to reconcile these cyclical components with rational expectations. In fact, 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 downward their expectations, 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 move on to explore the over-extrapolation mechanism in more detail in our data.

Before doing so, we also note that our results support a specific debt-financing channel in corporate investment. As such, our results complement other evidence on the relationship between investment and Tobin's Q (e.g., Tobin 1969, von Furstenberg 1977). The literature on the equity-financing channel (Bosworth 1975, Fischer and Merton 1984, Morck, Shleifer, and Vishny 1990, Blanchard, Rhee, and Summers 1993, Baker, Stein, and Wurgler 2003, Polk and Sapienza 2009) argues that stock prices contain elements of irrationality, so that the effective cost of external equity sometimes diverges from the cost of other forms of capital. Closer to our focus, Baker, Stein, and Wurgler (2003) use a proxy for equity dependence and document that firms that are more equity dependent invest more in response to stock market fluctuations. We share with this literature the view that the effective cost of some forms of external financing may diverge from that of others, and this might drive corporate investment. This literature has examined the cross sectional and time series correlations of corporate investment and stock markets. By contrast, we focus on cross sectional and time series correlations of corporate investment and credit markets.

5.3. 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 should stress that our purpose is *not* to "build a model to quantitatively match the data". Rather, we aim to take some off-the-shelf models to examine what existing theory has to say about credit markets and corporate investment cycles, and to articulate additional testable hypotheses that we will take to the data in the next section.

5.3.1. Framework

Consider a firm run by a risk-neutral owner who discounts the future by a factor $\beta < 1$, and with an infinite horizon. 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.

5.3.2. Solution

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:

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

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

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

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

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:

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

5.3.3. Calibration

To calibrate the theory and make it 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 without labor), $\delta = 0.15$, $\chi = 2$, interest rate $r = 0.04$ and discount factor $\beta = 1/(1+r)$. We report impulse response functions as produced by an $AR(1)$ process for TFP, $\log[A_t] = \rho \log[A_{t-1}] + \epsilon_t$, with $\epsilon_t \sim N(0, \sigma^2)$, $\rho \in [0,1]$, where we take $\rho = 0.7$ and $\sigma = 0.05$.

Figure 3 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.[19]

This pattern already rationalizes, in a qualitative sense, the empirical pattern documented in 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, by introducing a financial friction, and second, by considering a specific form of biased expectations, namely diagnostic expectations.

We begin by relaxing the assumption of rational expectation and introduce diagnostic expectations, because this formulation entails a straightforward modification of the baseline Q-theory. 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

[19]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, and as a result I/K converges to its steady state level, δ, from above.

Lucas critique. Fifth, it is a portable model of expectation formation in the sense of Rabin (2013).

Under diagnostic expectations it is possible to show that 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 (we show this explicitly in Section 5.3.4 below). For our calibration, we use $\theta = 0.7$, 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 4 reports the results and shows that, relative to rational expectations, diagnostic expectations produce larger swings in the variables, 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 larger a reversal under diagnostic expectations than under rational expectations. Remarkably, we note that even a relatively small deviation from rational expectations (i.e., $\theta = 0.7$) produces large responses in investment, capital, and I/K.

Next, we introduce financial frictions. We begin by noting that there is not a unique way to introduce financial frictions in dynamic models of macroeconomics and finance. 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 enables solving the model with standard numerical methods. In our calibration, we choose $\eta = 0.33$ $\tau = 0.35$, and η =2000, as is common in this literature (e.g., see Croce et al (2012)).

Figure 5 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 6 then brings all three settings together to facilitate comparison.[20]

As these figures show, both financial frictions and diagnostic expectations successfully generate larger fluctuations than the baseline frictionless model with rational expectations. Because our aim is not to match moments quantitatively, rather than playing with the parameters to attempt to match our regression results, in what follows we develop additional cross-sectional implications of the financial frictions and the diagnostic expectations model to sharpen our understanding of the economic channel driving our results.

To begin, 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 is a 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.

5.3.4. Rational vs biased expectations: An illustration

What about diagnostic expectations? We note that introducing diagnostic expectations in our setting generates additional cross-sectional predictions, relating forecast revisions and forecast errors

[20] 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.

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

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

implying 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)

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

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}, and 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 $\mathbb{E}_t\left[\pi_{t+k}-\mathbb{E}_t^{\theta}\left(\pi_{t+k}\right)\right]$ (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 $\mathbb{E}_t\left[\mathbb{E}_{t+k}^{\theta}\left(\pi_{t+T}\right)-\mathbb{E}_t^{\theta}\left(\pi_{t+T}\right)\right]$ (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, in our framework, the revision of forecasts, $\mathbb{E}_t\left[i_{t+1}-\mathbb{E}_t^{\theta}\left(i_{t+1}\right)\right]$, is such that

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

Thus, positive news about profits today make the firm invest more tomorrow and increase the predicted profits tomorrow, but 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. Biased Expectations and Investment

In this section, we attempt to explore the mechanism through which reversals in the real effects of credit market sentiment occur in our 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. As discussed in the previous section, 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.

To test these predictions we use data on analyst forecasts from IBES. 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. Following Clement and Tse (2005) and Hilary and Hsu (2013), we normalize this forecast revision by the stock price two days prior to the revision. We then take an average of all the normalized forecast revisions in each fiscal year, for each firm in our sample.[21]

In Figure 7, 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 0.37 with a t-statistic of 2.59 (p-value of 1.4%).

Does the credit market sentiment index reflect the revision of biased expectations? To examine this possibility, 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 and 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 8 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 38%. Therefore, in times of high credit market sentiment analysts are disproportionately more optimistic about speculative-grade bond issuers relative to investment grade bond issuers, again consistent with over-extrapolation.

Of course, over-extrapolation also implies that following a credit market boom analysts systematically revise their forecasts downward. Specifically, we compute EPS forecast revision 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 $t+k-1$ (two-year ahead forecast). We find a negative correlation between this EPS forecast revision variable and credit market sentiment.

[21] 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.

The correlation coefficient is statistically significant for $k = 2$, $k = 3$, and $k = 4$, and it increases in magnitude with k. Figure 9 reports the correlation for $k = 3$.

As a result, credit market sentiment in the aggregate appears to be tightly linked to biased analyst expectations and their subsequent forecast revisions. Next, we move to 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 10 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 that were 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 $t + 3$, $t + 4$, and $t + 5$ and strongly statistically significant in year $t + 5$. Table 11 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 $t + 3$ to $t + 5$ 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 in years $t + 3$, $t + 4$, and $t + 5$ and strongly statistically significant in year $t + 5$.

Finally, 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 12, 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 10 and 11). 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, forecast revisions predict forecast errors in year 5 more negatively following a credit market boom, and this relationship is statistically significant. 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 $t+5$.

7. 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. Our results show that credit market cycles beget corporate investment cycles. In the short run, a credit market boom in year t comes with 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. The reason is that 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 beget 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 across the board for all types of firms, irrespective of financial frictions. Third, we find that the predictable mean reversion in credit market sentiment—documented elsewhere—also produces predictable reversals in its real effects on corporate investment and financing. These last pieces of evidence point to the need to incorporate a 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.

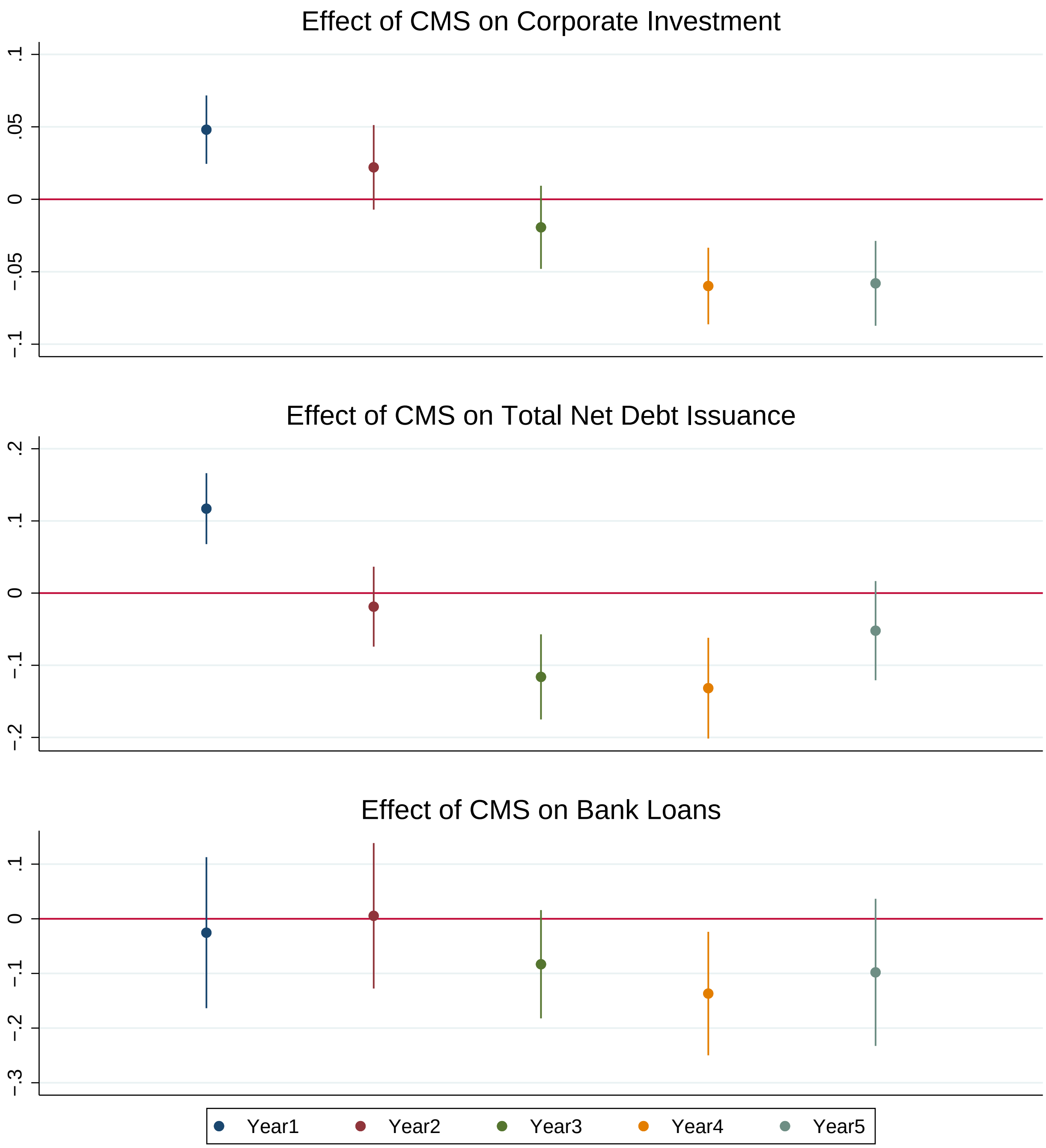

Figure 2
Effect of Credit Market Sentiment
This figure plots the coefficients on the Credit Market Sentiment Variable (CMS) when predicting future corporate investment (top panel), total net debt issuance (middle panel) and new bank loans (bottom panel). All independent variables from our baseline specification 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.

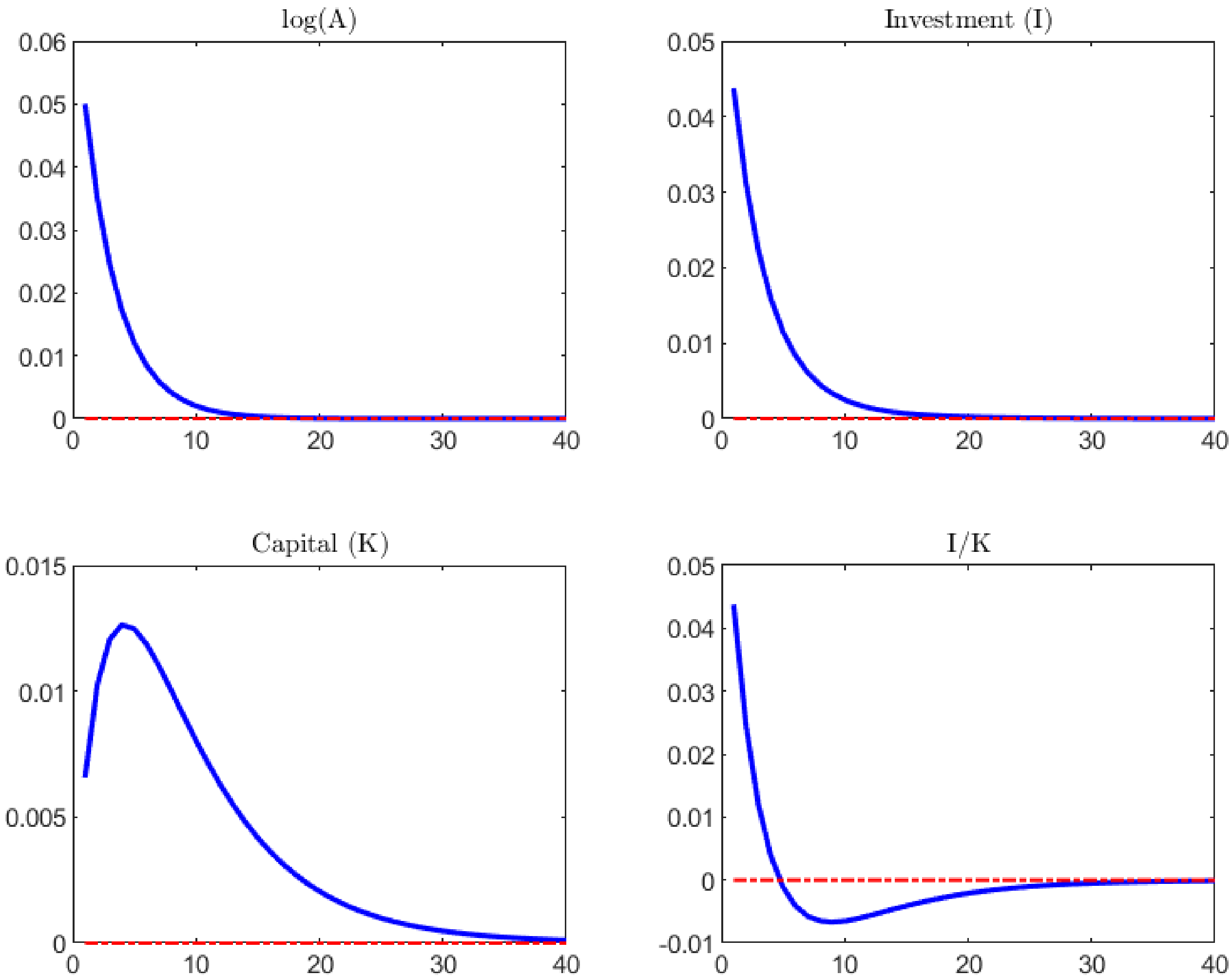

Figure 3
IRF under Rational Expectations
This figure plots the impulse response function of neoclassical Q-theory under rational expectations (RE). All variables are measured at time T=0. Year “k” (k=1...5) means the dependent variable is measured at time T+k=k. The economic magnitude (y axis) can be 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.

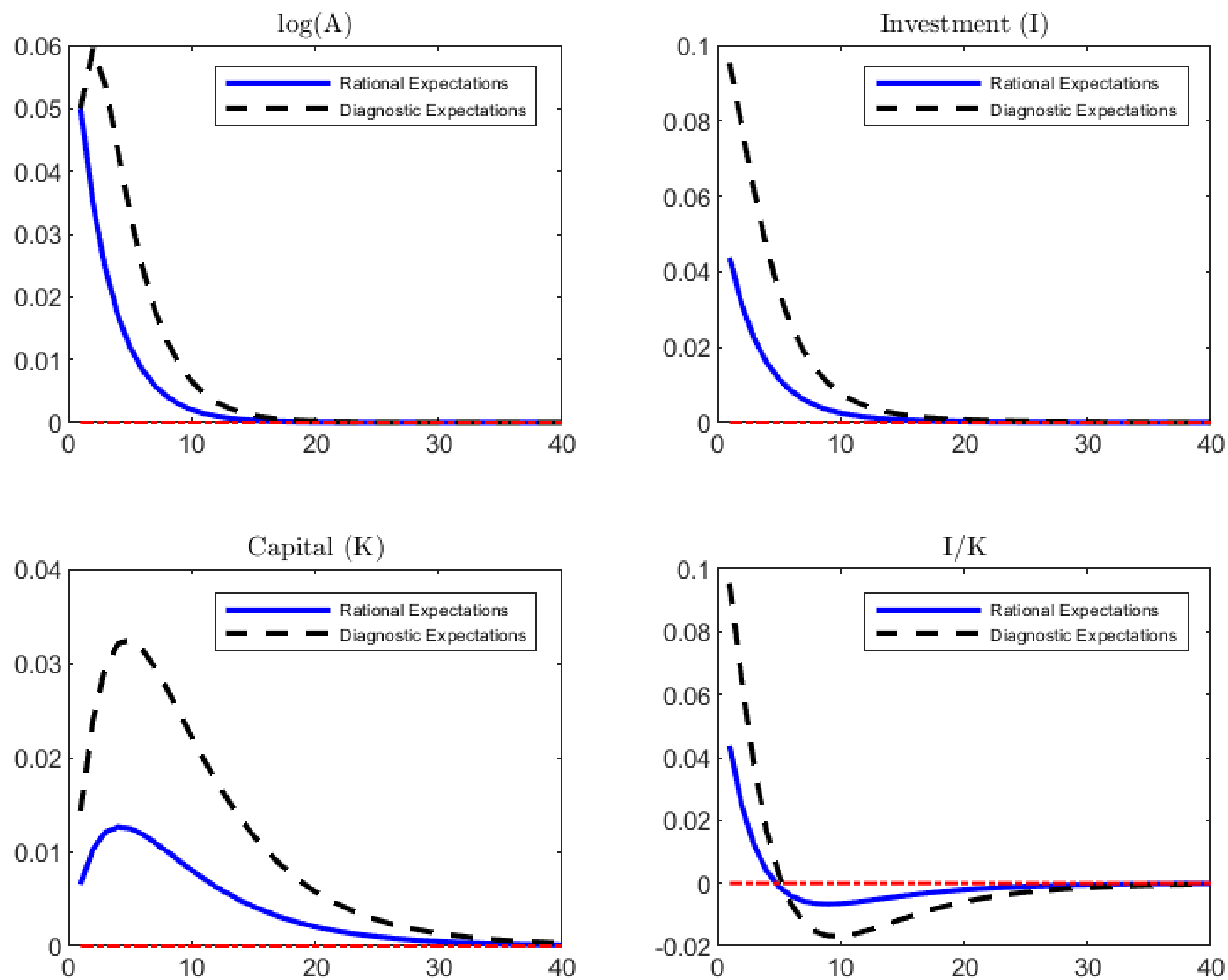

Figure 4
IRF under Rational Expectations and under Diagnostic Expectations
This figure plots the impulse response function of neoclassical Q-theory under rational expectations (RE) and of Q-theory under diagnostic expectations (DE). All variables are measured at time T=0. Year “k” (k=1...5) means the 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.

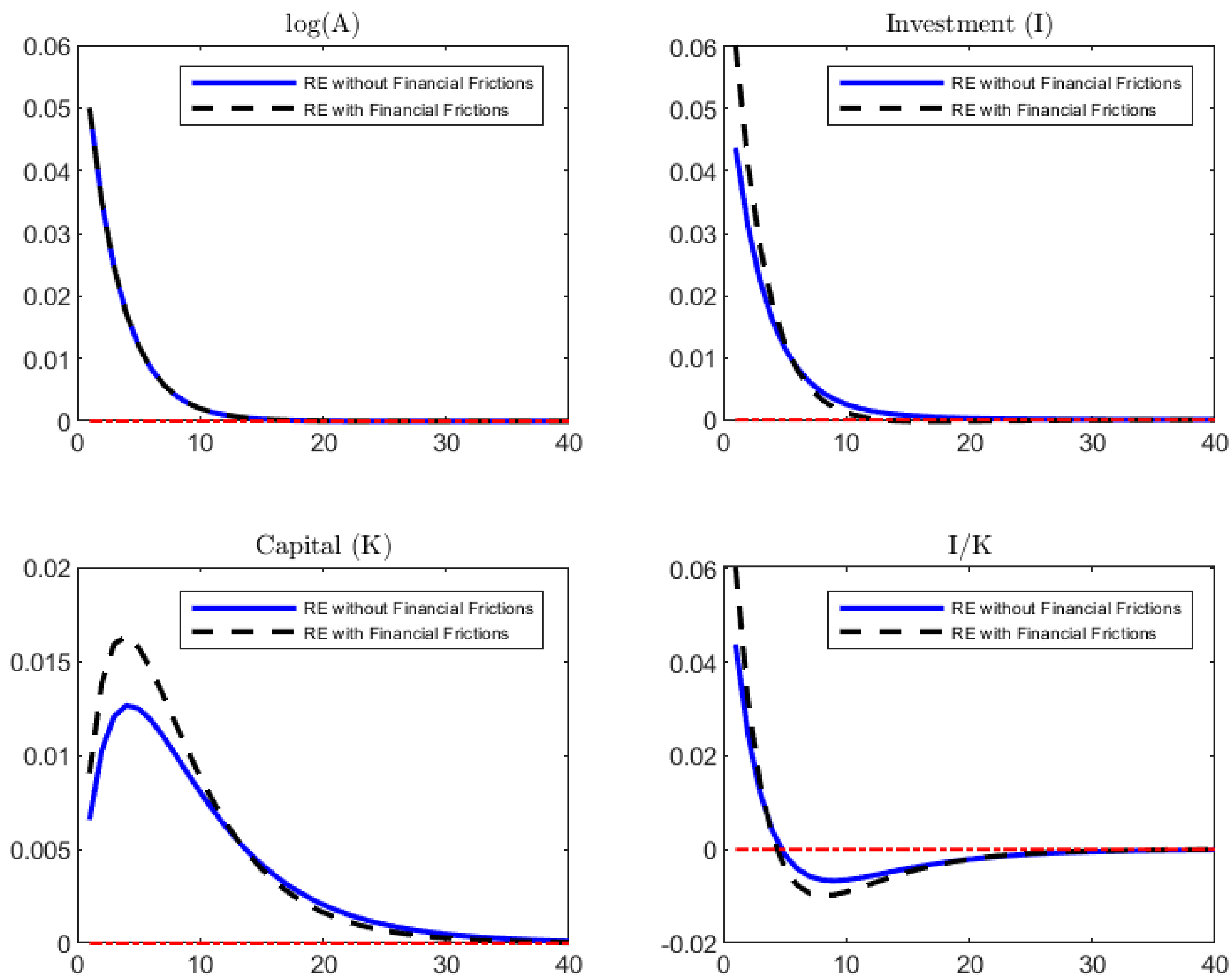

Figure 5

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.

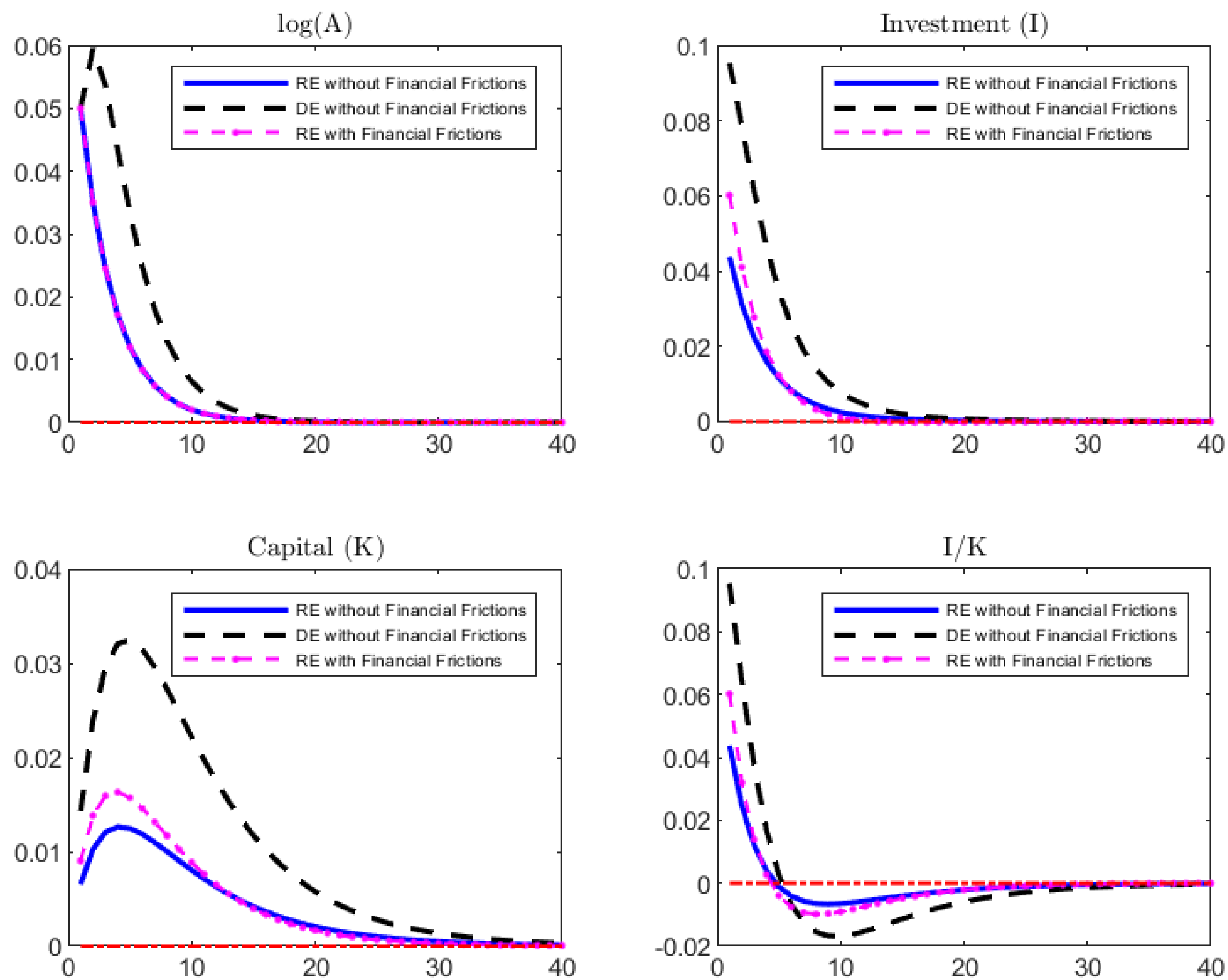

Figure 6
IRF under Rational Expectations with and without Financial Frictions, and IRF under Diagnostic Expectations
This figure plots the impulse response function of neoclassical Q-theory under rational expectations (RE) without collateral constraint and with collateral constraint, and of Q-theory 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.

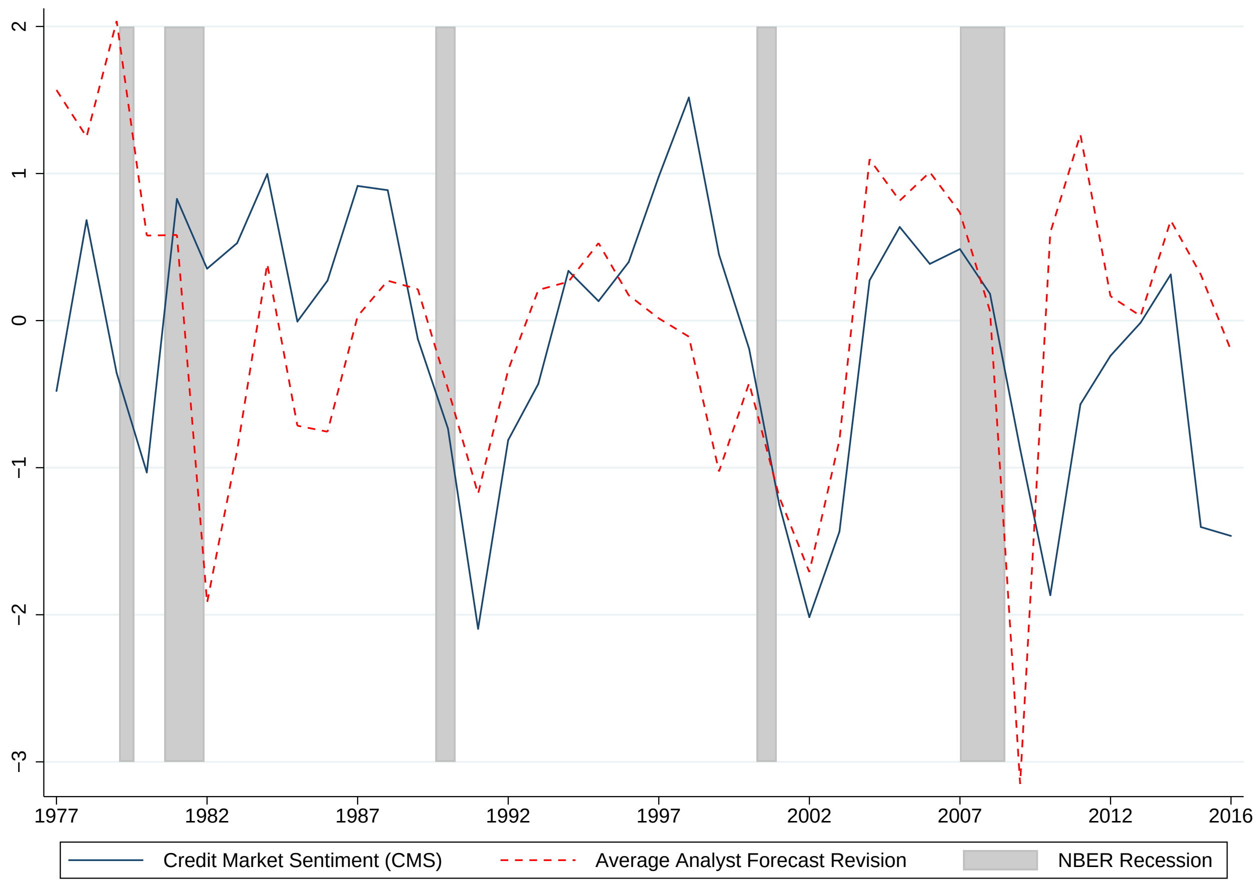

Figure 7
Credit Market Sentiment and Analyst Forecast Revisions
The solid line in this figure plots the credit market sentiment index of Greenwood and Hanson (2013). This index is calculated as the difference between average default probabilities of firms with the highest debt issuance and firms with 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 correlation between the two series is 27%. The shaded areas are NBER recessions.

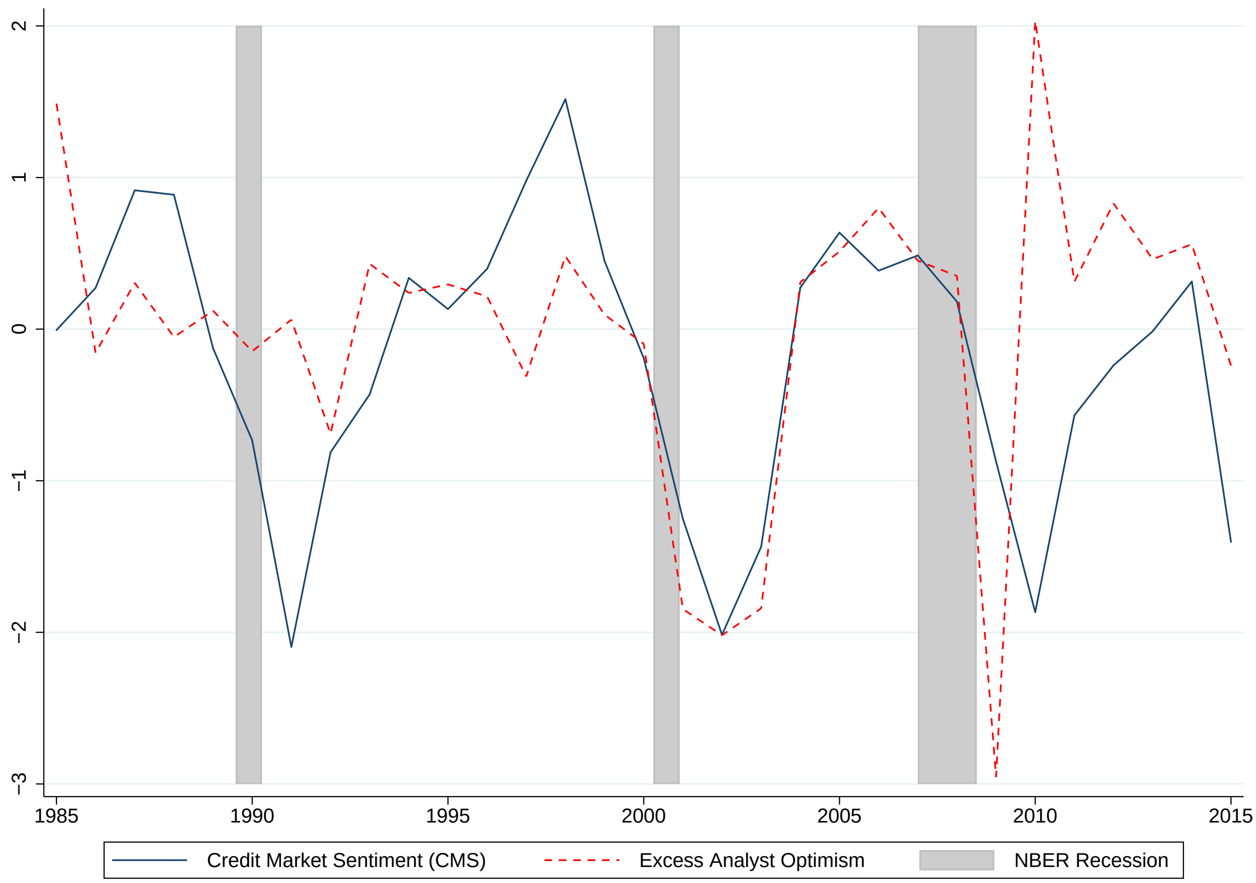

Figure 8
Credit Market Sentiment and Excess Analyst Optimism
The solid line in this figure plots the credit market sentiment index of Greenwood and Hanson (2013). The dashed line plots the average analyst (EPS) forecast of issuers of speculative-grade bonds minus the average analyst forecast of investment-grade bond issuers. The correlation between the two series is 38%. The shaded areas are NBER recessions.

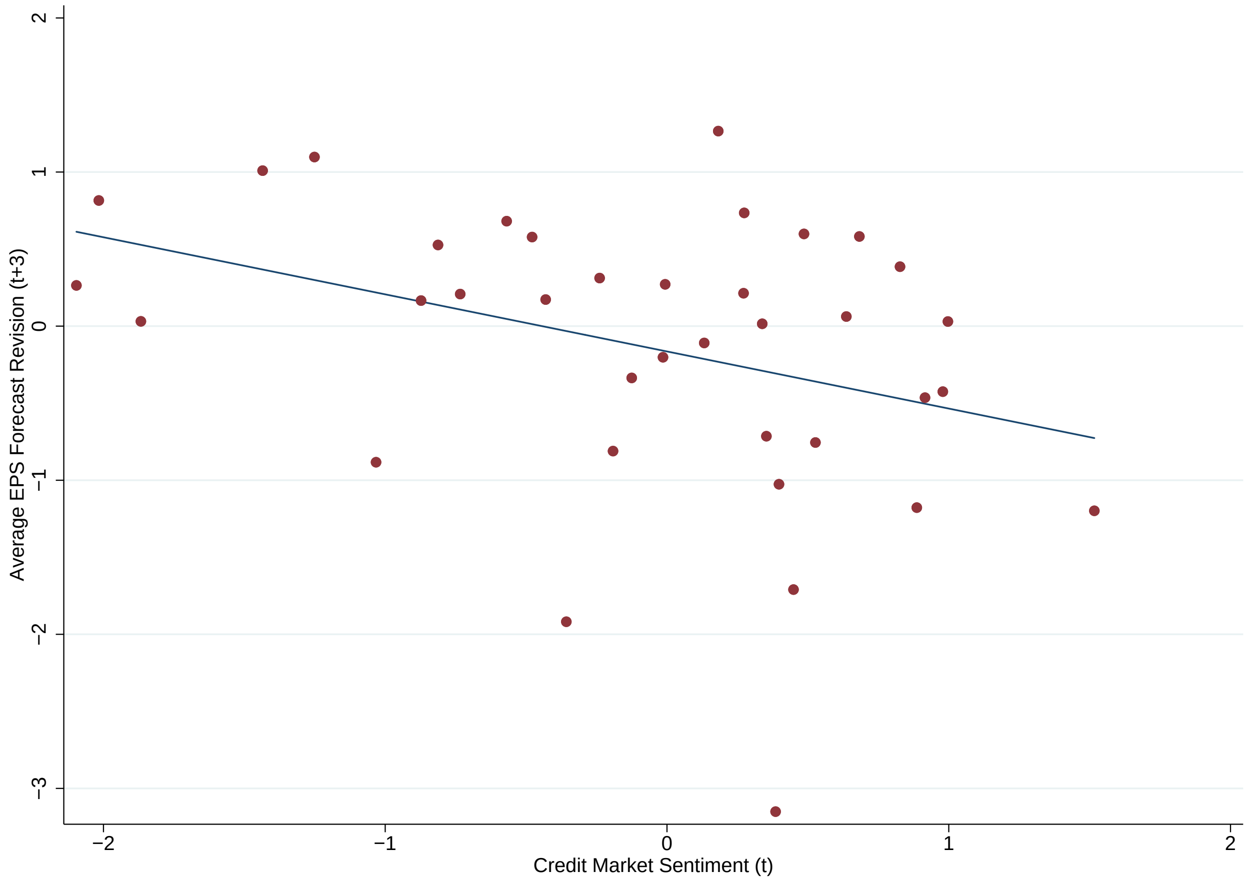

Figure 9
Credit Market Sentiment Predicts Downward Forecast Revisions
Each point on this scatter plot represents the credit market sentiment index of Greenwood and Hanson (2013) in a particular year t (horizontal axis) and the average of all analyst EPS forecast revisions in year $t + 3$. The sample period is 1985 to 2015. The slope of the regression line is -0.034 with a t-statistics of -2.49.

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 coefficients 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 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.

	Total investment			Investment in physical capital			Investment in intangible capital		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CMS	0.051***	0.039***	0.048***	0.068***	0.048***	0.064***	0.042***	0.032***	0.035***
	(3.27)	(3.29)	(3.99)	(3.33)	(3.36)	(4.44)	(2.97)	(2.64)	(2.81)
Tobin's q	0.712***	0.599***	0.691***	0.639***	0.519***	0.629***	0.718***	0.611***	0.668***
	(30.95)	(25.50)	(23.76)	(20.39)	(18.85)	(16.56)	(22.51)	(18.91)	(18.03)
Cash flow to assets	0.238***	0.128***	0.143***	0.306***	0.184***	0.193***	0.187***	0.059**	0.078***
	(12.16)	(6.97)	(6.38)	(10.85)	(6.76)	(5.60)	(9.99)	(2.53)	(3.05)
Log total assets		-0.646***	-0.678***		-0.853***	-0.893***		-0.419***	-0.449***
		(-20.45)	(-18.25)		(-22.82)	(-20.79)		(-13.26)	(-12.06)
Cash to assets		0.276***	0.302***		0.247***	0.301***		0.264***	0.281***
		(16.28)	(15.50)		(10.29)	(11.54)		(11.13)	(10.43)
Book leverage		-0.120***	-0.096***		-0.190***	-0.148***		-0.053***	-0.046***
		(-10.13)	(-8.09)		(-13.55)	(-10.44)		(-4.00)	(-3.39)
Sales growth		0.124***	0.133***		0.129***	0.145***		0.126***	0.134***
		(12.75)	(13.66)		(11.30)	(12.28)		(12.61)	(12.32)
ROA		0.123***	0.088***		0.135***	0.122***		0.148***	0.095***
		(6.77)	(4.17)		(5.32)	(3.77)		(7.77)	(4.51)
LEI			-0.034**			-0.035*			-0.030**
			(-2.29)			(-1.90)			(-1.99)
JLN index			0.024			0.003			0.043***
			(1.27)			(0.11)			(2.95)
BW index			-0.054***			-0.064***			-0.043***
			(-4.75)			(-3.89)			(-4.18)
Default spread			-0.060***			-0.031**			-0.084***
			(-5.21)			(-2.25)			(-6.62)
Credit quality			-0.104***			-0.150***			-0.060***
			(-9.15)			(-10.60)			(-5.01)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	134,580	132,730	112,010	136,674	134,753	112,407	134,830	132,964	112,187
R^2	0.122	0.169	0.184	0.078	0.129	0.147	0.101	0.123	0.123

Table 4
Conditioning on Debt Dependence

This table presents coefficients 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 two measures of debt dependence (private versus public status in the first three columns, and whether the firm does R&D in the last three columns). In the first column, we combine data on public and private firms and we add an interaction between credit market sentiment and a private firm indicator to our baseline specification. Columns two and three run our baseline specification separately on the sample of public firms and the sample of private firms. In column four, we add an interaction between credit market sentiment and an indicator variable that equals one if the firm has never had positive R&D expenses in the past. In the last two columns we run our baseline specification separately on the sample of firms with R&D and the sample of firms without R&D. 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 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: Dependent variable is total corporate investment					
	Public and private	Public only	Private only	Public only	Public with R&D	Public no R&D
CMS	0.054***	0.060***	0.217**	0.031**	0.041***	0.054***
	(2.82)	(3.98)	(2.54)	(2.16)	(3.14)	(3.83)
CMS x Private firm indicator	0.226**					
	(2.37)					
CMS x No R&D indicator				0.033**		
				(2.50)		
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	181,831	134,425	47,406	112,010	59,642	52,154
R^2	0.042	0.083	0.054	0.184	0.189	0.187

	Panel B: Dependent variable is total net debt issuance					
	Public and private	Public only	Private only	Public only	Public with R&D	Public no R&D
CMS	0.123***	0.113***	0.150***	0.083***	0.093***	0.150***
	(4.70)	(4.94)	(4.31)	(2.74)	(3.20)	(5.04)
CMS x Private firm indicator	0.006					
	(0.19)					
CMS x No R&D indicator				0.071**		
				(2.38)		
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	183,263	135,132	48,131	112,512	59,961	52,336
R^2	0.059	0.082	0.139	0.105	0.096	0.120

Table 5
Conditioning on Financial Constraints

This table presents coefficients 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). In columns 1, 4, and 7, we use the full sample and include interactions of credit market sentiment with the financial constraints proxies. In the remaining columns, we run our baseline specification separately on samples of firms that are less financially constrained (columns 2, 5, 8) and the samples of firms that are more financially constrained (columns 3, 6, 9). 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: Dependent variable is total corporate investment								
	Below HP median	Above HP median	Full sample	Below WW median	Above WW median	Full sample	With credit rating	Without credit rating	Full sample
CMS	0.025*	0.069***	0.053***	0.036***	0.059***	0.051***	0.028*	0.055***	0.031**
	(1.78)	(5.48)	(4.73)	(2.80)	(4.49)	(4.22)	(1.85)	(4.28)	(2.13)
CMS x HP			0.019**						
			(2.55)						
Hadlock and Pierce (HP)			-0.115**						
			(-1.99)						
CMS x WW						0.011***			
						(2.65)			
Whited and Wu (WW)						-0.154***			
						(-3.27)			
CMS x No credit rating									0.028**
									(2.52)
No credit rating									0.291***
									(6.35)
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	56,003	55,127	112,010	42,061	41,737	85,259	21,452	51,574	73,806
R^2	0.193	0.162	0.184	0.196	0.154	0.173	0.146	0.170	0.183

Table 5
Conditioning on Financial Constraints (Continued)

	Panel B: Dependent variable is total net debt issuance								
	Below HP median	Above HP median	Full sample	Below WW median	Above WW median	Full sample	With credit rating	Without credit rating	Full sample
CMS	0.084***	0.151***	0.130***	0.100***	0.167***	0.133***	0.082***	0.148***	0.096***
	(3.07)	(5.56)	(5.23)	(3.22)	(5.96)	(4.71)	(2.63)	(5.07)	(2.71)
CMS x HP			0.032*						
			(1.75)						
Hadlock and Pierce (HP)			0.592***						
			(5.42)						
CMS x WW						0.028*			
						(1.78)			
Whited and Wu (WW)						-0.394***			
						(-3.90)			
CMS x No credit rating									0.056*
									(1.69)
No credit rating									0.204**
									(2.03)
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	55,996	55,121	112,512	42,054	41,736	85,722	21,606	51,882	74,269
R^2	0.102	0.105	0.106	0.102	0.111	0.102	0.114	0.102	0.112

Table 6
Long-Term Effects on Corporate Investment

This table presents coefficients 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 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: Total investment				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.048***	0.022	-0.019	-0.060***	-0.058***
	(3.99)	(1.48)	(-1.32)	(-4.44)	(-3.88)
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	112,010	100,716	91,469	83,407	76,296
R^2	0.184	0.107	0.072	0.064	0.061

	Panel B: Investment in physical capital				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.064***	0.019	-0.019	-0.055***	-0.048***
	(4.44)	(1.40)	(-1.31)	(-3.89)	(-2.85)
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	112,407	102,140	92,828	84,725	77,548
R^2	0.147	0.096	0.071	0.063	0.060

	Panel C: Investment in intangible capital				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.035***	0.024	-0.017	-0.061***	-0.062***
	(2.81)	(1.34)	(-1.03)	(-3.82)	(-4.15)
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	112,187	100,874	91,618	83,537	76,414
R^2	0.123	0.064	0.039	0.035	0.033

Table 7
Long-Term Effects on Debt Issuance

This table presents coefficients 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 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: Total net debt issuance				
	Year 1	Year 2	Year 3	Year 4	Year 5
Credit market sentiment	0.111***	-0.025	-0.123***	-0.131***	-0.044
	(4.54)	(-0.93)	(-4.16)	(-3.68)	(-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	113,206	103,139	93,780	85,610	78,388
R^2	0.104	0.064	0.041	0.031	0.025

	Panel B: Long-term net debt issuance				
	Year 1	Year 2	Year 3	Year 4	Year 5
Credit market sentiment	0.113***	0.011	-0.051**	-0.077***	-0.055**
	(6.72)	(0.74)	(-2.52)	(-3.44)	(-2.33)
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	113,121	102,973	93,588	85,407	78,190
R^2	0.112	0.064	0.035	0.024	0.019

	Panel C: Short-term net debt issuance				
	Year 1	Year 2	Year 3	Year 4	Year 5
Credit market sentiment	-0.002	-0.038**	-0.070***	-0.053***	0.009
	(-0.20)	(-2.31)	(-5.30)	(-3.21)	(0.56)
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	113,106	102,960	93,580	85,399	78,182
R^2	0.058	0.036	0.028	0.024	0.018

Table 8
Long-Term Effects on Loan Issuance

This table presents coefficients 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 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 Dealscan loans				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	-0.025	0.005	-0.083*	-0.137**	-0.098
	(-0.36)	(0.08)	(-1.65)	(-2.37)	(-1.43)
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	63,485	55,978	49,598	43,988	39,109
R^2	0.010	0.005	0.009	0.008	0.006

	Panel B: Only loan originations				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.031	0.021	-0.059	-0.143***	-0.132**
	(0.61)	(0.61)	(-1.01)	(-2.72)	(-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	63,485	55,978	49,598	43,988	39,109
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	-0.080	-0.026	-0.111	-0.127	-0.058
	(-0.79)	(-0.23)	(-1.21)	(-1.30)	(-0.55)
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	63,485	55,978	49,598	43,988	39,109
R^2	0.011	0.008	0.009	0.009	0.007

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

This table presents coefficients 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. In Panel A1 we use only the firms in the top quintile with respect to the Hadlock and Pierce (2010) index (HP), and in Panel A2, we use only the firms in the bottom quintile. In Panel B1 we use only the firms in the top quintile of CEO overconfidence, and in Panel B2 we use only the firms in the bottom quintile. 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 A1: Effect on investment for firms with high financial constraints (HP)				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.064***	0.030*	-0.029	-0.072***	-0.062***
	(4.93)	(1.68)	(-1.25)	(-3.40)	(-3.25)
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	14,239	12,056	10,503	9,256	8,208
R^2	0.112	0.031	0.015	0.011	0.015

	Panel A2: Effect on investment for firms with low financial constraints (HP)				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.021	0.011	-0.021	-0.047***	-0.045***
	(1.39)	(0.82)	(-1.51)	(-3.36)	(-2.94)
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	28,455	26,446	24,703	23,143	21,638
R^2	0.168	0.098	0.069	0.059	0.054

	Panel B1: Effect on debt issuance for firms with high financial constraints (HP)				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.119***	-0.042	-0.155***	-0.103**	-0.029
	(3.00)	(-0.94)	(-3.51)	(-1.97)	(-0.47)
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	14,332	12,249	10,701	9,452	8,408
R^2	0.090	0.036	0.017	0.008	0.008

	Panel B2: Effect on debt issuance for firms with low financial constraints (HP)				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.072**	-0.003	-0.061**	-0.086***	-0.064**
	(2.56)	(-0.15)	(-2.17)	(-2.76)	(-1.96)
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	28,555	26,888	25,130	23,560	22,061
R^2	0.087	0.053	0.036	0.025	0.022

Table 10
Effect on Corporate Investment, Conditional on Over-extrapolation

This table presents coefficients 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. 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 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: Firms with highest analyst forecast revisions				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.071**	0.014	-0.013	-0.054**	-0.114***
	(2.24)	(0.39)	(-0.46)	(-2.00)	(-6.42)
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	4,777	4,258	3,891	3,562	3,232
R^2	0.148	0.073	0.049	0.044	0.042

	Panel B: Firms with lowest analyst forecast revisions				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.031	-0.002	0.011	-0.034	-0.035
	(1.39)	(-0.04)	(0.31)	(-1.33)	(-1.50)
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	4,438	3,712	3,171	2,728	2,406
R^2	0.117	0.081	0.026	0.025	0.020

	Panel C: Combined samples				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS x High-revision dummy	0.040	0.016	-0.024	-0.020	-0.079***
	(1.16)	(0.32)	(-0.61)	(-0.82)	(-2.83)
CMS	0.031	-0.002	0.011	-0.034	-0.035
	(1.39)	(-0.04)	(0.31)	(-1.33)	(-1.50)
High-revision dummy	0.120**	0.078	0.147*	0.031	0.062
	(2.05)	(0.78)	(1.89)	(0.47)	(1.22)
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	9,215	7,970	7,062	6,290	5,638
R^2	0.182	0.104	0.051	0.044	0.038

Table 11
Effect on Debt Issuance, Conditional on Over-extrapolation

This table presents coefficients 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. 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 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: Firms with highest analyst forecast revisions				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.181***	-0.033	-0.089*	-0.143***	-0.130***
	(4.00)	(-0.54)	(-1.71)	(-2.79)	(-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	4,800	4,363	3,992	3,661	3,316
R^2	0.045	0.021	0.008	0.010	0.009

	Panel B: Firms with lowest analyst forecast revisions				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	-0.043	-0.099	-0.079	-0.072	0.039
	(-1.15)	(-1.44)	(-1.06)	(-1.39)	(0.53)
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	4,457	3,806	3,255	2,804	2,479
R^2	0.057	0.021	0.008	0.005	0.013

	Panel C: Combined samples				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS x High-revision dummy	0.224***	0.065	-0.009	-0.072	-0.169***
	(4.91)	(0.73)	(-0.11)	(-1.63)	(-2.63)
CMS	-0.043	-0.099	-0.079	-0.072	0.039
	(-1.15)	(-1.44)	(-1.06)	(-1.39)	(0.53)
High-revision dummy	0.200*	0.244*	0.217*	0.145	0.034
	(1.79)	(1.70)	(1.69)	(1.33)	(0.38)
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	9,257	8,169	7,247	6,465	5,795
R^2	0.073	0.033	0.014	0.010	0.011

Table 12
Effect on Forecast Error, Conditional on Over-extrapolation

This table presents coefficients 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 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.

	Year 1	Year 2	Year 3	Year 4	Year 5
CMS x Forecast revision	0.003	0.002	0.009	0.002	-0.018**
	(0.49)	(0.40)	(1.01)	(0.30)	(-1.98)
CMS	-0.010	-0.007	-0.050	-0.024	0.069
	(-0.22)	(-0.18)	(-0.92)	(-0.46)	(1.28)
Forecast revision	0.023***	0.006	0.001	-0.016**	-0.021**
	(6.50)	(1.46)	(0.14)	(-2.27)	(-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	44,576	41,312	17,576	7,336	4,320
R^2	0.203	0.064	0.035	0.025	0.027

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:

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

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

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

The Lagrangian is

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

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

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

and consider the definition of profits, $\Pi_t = A_t K_t^{\alpha} - C(I_t, K_t) K_t - I_t$, 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 you 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:

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

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

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

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

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

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

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

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: Tables

Table C1
Controlling for Firm-Level Credit Worthiness

This table presents coefficients 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	0.048***	0.039***	0.047***	0.048***
	(3.99)	(2.99)	(4.36)	(4.47)
Credit quality	-0.104***			
	(-9.15)			
Campbell, Hilsher and Szilagyi (2008) index		-0.152***		
		(-12.29)		
Ohlson (1980) O score			0.007	
			(0.31)	
Altman (1968) Z score				-0.092***
				(-5.31)
Firm-level controls	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
N	112,010	101,330	127,336	127,498
R^2	0.184	0.185	0.174	0.175

Table C2
Long-Term Effects on Sources of External Financing Using All Firms

This table presents coefficients 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	0.472***	0.128*	-0.096	-0.326***	-0.378***
	(6.11)	(1.79)	(-1.18)	(-3.37)	(-3.73)
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	101,728	94,126	86,524	79,848	73,821
R^2	0.077	0.049	0.027	0.017	0.015

	Panel B: Net Equity Repurchases				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.240***	0.127	0.139*	-0.006	-0.164*
	(2.72)	(1.20)	(1.67)	(-0.10)	(-1.75)
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	100,763	93,338	85,933	79,433	73,526
R^2	0.092	0.046	0.032	0.025	0.022

	Panel C: Net External Financing				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.260**	0.013	-0.247**	-0.313***	-0.184**
	(2.55)	(0.12)	(-2.43)	(-3.38)	(-2.04)
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	95,108	88,103	81,107	74,952	69,318
R^2	0.087	0.051	0.040	0.032	0.028

Table C3
Long-Term Effects on Sources of External Financing Using Firms In Top Size Decile

This table presents the same tests as in Table C2 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	0.312***	0.346***	0.278***	-0.027	-0.416***
	(3.29)	(4.12)	(3.76)	(-0.31)	(-3.63)
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	13,094	12,682	12,148	11,633	11,146
R^2	0.060	0.043	0.029	0.014	0.012

	Panel B: Net Equity Repurchases				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.325***	0.205**	-0.053	-0.365***	-0.512***
	(4.39)	(2.37)	(-0.54)	(-3.58)	(-5.02)
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	12,939	12,538	12,008	11,517	11,046
R^2	0.127	0.093	0.075	0.074	0.074

	Panel C: Net External Financing				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	-0.033	0.152	0.310***	0.375***	0.163
	(-0.28)	(1.27)	(2.66)	(3.25)	(1.33)
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	12,117	11,750	11,261	10,791	10,348
R^2	0.071	0.051	0.049	0.042	0.029

Table C4
Long-Term Effects on Sources of External Financing Using Firms In Bottom Nine Size Deciles

This table presents the same tests as in Table C2 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	0.501***	0.097	-0.148*	-0.361***	-0.351***
	(6.22)	(1.26)	(-1.65)	(-3.30)	(-3.22)
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	88,404	81,247	74,208	68,022	62,503
R^2	0.082	0.051	0.028	0.018	0.015

	Panel B: Net Equity Repurchases				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.234**	0.123	0.180**	0.065	-0.101
	(2.43)	(1.03)	(2.04)	(0.95)	(-1.03)
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	87,609	80,603	73,751	67,739	62,324
R^2	0.093	0.041	0.027	0.020	0.016

	Panel C: Net External Financing				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.306***	-0.009	-0.337***	-0.420***	-0.225**
	(2.65)	(-0.07)	(-2.93)	(-3.69)	(-2.12)
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	82,772	76,155	69,672	63,973	58,809
R^2	0.090	0.049	0.037	0.029	0.025

Table C5
Long-Term Effects on Investment, Conditioning on Firm Size

This table presents coefficients 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	0.048***	0.022	-0.019	-0.060***	-0.058***
	(3.99)	(1.48)	(-1.32)	(-4.44)	(-3.88)
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	112,010	100,716	91,469	83,407	76,296
R^2	0.184	0.107	0.072	0.064	0.061

	Panel B: Firms in Top Size Decile				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.022	0.018	-0.003	-0.039**	-0.045***
	(1.28)	(1.22)	(-0.20)	(-2.19)	(-2.74)
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	14,608	13,782	13,047	12,392	11,758
R^2	0.172	0.118	0.086	0.071	0.056

	Panel C: Firms in Bottom Nine Size Deciles				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.055***	0.026	-0.019	-0.060***	-0.058***
	(4.44)	(1.64)	(-1.24)	(-4.49)	(-3.72)
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	97,182	86,733	78,244	70,837	64,375
R^2	0.181	0.100	0.065	0.055	0.051

Table C6
Long-Term Effects on Corporate Investment by Sector

This table presents coefficients 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	0.040***	0.033***	0.008	-0.008	0.010
	(2.78)	(2.59)	(0.68)	(-0.64)	(0.84)
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	10,358	9,465	8,718	8,012	7,397
R^2	0.131	0.087	0.065	0.051	0.045
	Sector 2: Consumer Durables – Cars, TV's, Furniture, Household Appliances				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.064***	-0.006	-0.051***	-0.059***	-0.012
	(3.52)	(-0.32)	(-2.89)	(-3.55)	(-0.52)
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	4,566	4,160	3,843	3,543	3,259
R^2	0.170	0.111	0.068	0.059	0.051
	Sector 3: Manufacturing – Machinery, Trucks, Planes, Off Furn, Paper, Com Printing				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.042***	0.025*	-0.015	-0.060***	-0.055***
	(3.22)	(1.78)	(-0.86)	(-3.20)	(-2.73)
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	21,195	19,534	18,066	16,723	15,463
R^2	0.146	0.088	0.057	0.052	0.045
	Sector 4: Oil, Gas, and Coal Extraction and Products				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.024	-0.001	-0.023	-0.133***	-0.158***
	(0.74)	(-0.03)	(-0.42)	(-2.66)	(-3.42)
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	6,097	5,398	4,824	4,383	3,976
R^2	0.192	0.093	0.070	0.068	0.062

Table C6
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	0.054***	0.030*	-0.024	-0.050***	-0.058***
	(2.66)	(1.72)	(-1.21)	(-2.89)	(-2.91)
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	4,213	3,902	3,638	3,406	3,186
R^2	0.139	0.086	0.066	0.054	0.039
	Sector 6: Business Equipment – Computers, Software, and Electronic Equipment				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.058***	0.060*	0.000	-0.067***	-0.070***
	(3.36)	(1.87)	(0.00)	(-2.78)	(-3.36)
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	19,560	17,385	15,641	14,154	12,886
R^2	0.253	0.140	0.100	0.090	0.086
	Sector 7: Telephone and Television Transmission				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.070	0.063	0.008	-0.091***	-0.093**
	(1.51)	(1.25)	(0.17)	(-2.91)	(-2.19)
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	2,878	2,512	2,219	1,974	1,769
R^2	0.216	0.110	0.065	0.077	0.085
	Sector 9: Wholesale, Retail, and Some Services (Laundries, Repair Shops)				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.046***	0.002	-0.040**	-0.055***	-0.037**
	(3.11)	(0.18)	(-2.42)	(-3.33)	(-2.33)
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	15,991	14,312	12,992	11,827	10,817
R^2	0.232	0.168	0.112	0.100	0.099
	Sector 10: Healthcare, Medical Equipment, and Drugs				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	-0.005	-0.017	-0.013	-0.030	-0.059***
	(-0.21)	(-0.78)	(-0.63)	(-1.40)	(-2.63)
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	10,027	8,821	7,884	7,077	6,382
R^2	0.182	0.107	0.070	0.059	0.059
	Sector 12: Other – Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.063***	0.009	-0.036*	-0.069***	-0.076***
	(3.38)	(0.52)	(-1.93)	(-3.89)	(-3.42)
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	17,118	15,221	13,639	12,298	11,155
R^2	0.174	0.098	0.062	0.056	0.060

Table C7
Long-Term Effects on Debt Issuance by Sector

This table presents coefficients 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	0.103***	0.006	-0.060**	-0.039	0.042
	(3.71)	(0.23)	(-2.07)	(-1.02)	(1.14)
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	10,397	9,573	8,822	8,120	7,495
R^2	0.107	0.071	0.042	0.030	0.022
	Sector 2: Consumer Durables – Cars, TV's, Furniture, Household Appliances				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.198***	-0.081*	-0.183***	-0.067	0.074
	(3.52)	(-1.65)	(-3.81)	(-1.11)	(1.05)
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	4,581	4,217	3,896	3,601	3,314
R^2	0.111	0.061	0.039	0.034	0.031
	Sector 3: Manufacturing – Machinery, Trucks, Planes, Off Furn, Paper, Com Printing				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.086**	-0.018	-0.104**	-0.134***	-0.014
	(2.32)	(-0.50)	(-2.44)	(-2.61)	(-0.26)
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	21,268	19,788	18,318	16,983	15,718
R^2	0.097	0.068	0.036	0.028	0.019
	Sector 4: Oil, Gas, and Coal Extraction and Products				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.089	-0.019	-0.142*	-0.277***	-0.195***
	(1.52)	(-0.26)	(-1.81)	(-3.69)	(-2.74)
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	6,108	5,496	4,915	4,469	4,062
R^2	0.122	0.066	0.055	0.050	0.041

Table C7
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	0.103**	0.010	-0.108*	-0.149***	-0.115**
	(2.13)	(0.23)	(-1.83)	(-3.00)	(-2.29)
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	4,231	3,964	3,701	3,471	3,251
R^2	0.077	0.051	0.026	0.028	0.019

	Sector 6: Business Equipment – Computers, Software, and Electronic Equipment				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.096***	0.015	-0.118***	-0.162***	-0.082**
	(3.69)	(0.33)	(-2.75)	(-5.07)	(-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	19,694	17,687	15,940	14,439	13,143
R^2	0.113	0.066	0.044	0.029	0.027

	Sector 7: Telephone and Television Transmission				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.269***	0.162**	0.030	-0.147**	-0.133*
	(3.58)	(2.41)	(0.50)	(-2.12)	(-1.85)
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	2,886	2,558	2,272	2,022	1,813
R^2	0.139	0.087	0.046	0.054	0.054

	Sector 9: Wholesale, Retail, and Some Services (Laundries, Repair Shops)				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.127***	-0.045	-0.158***	-0.108***	-0.026
	(3.74)	(-1.31)	(-4.03)	(-2.58)	(-0.63)
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	16,067	14,485	13,151	11,979	10,959
R^2	0.123	0.078	0.049	0.040	0.033

	Sector 10: Healthcare, Medical Equipment, and Drugs				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.037	-0.048	-0.076*	-0.090**	-0.093**
	(0.83)	(-1.34)	(-1.86)	(-2.17)	(-2.23)
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	10,082	9,017	8,067	7,254	6,564
R^2	0.090	0.051	0.036	0.026	0.028

	Sector 12: Other – Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment				
	Year 1	Year 2	Year 3	Year 4	Year 5
CMS	0.168***	-0.047	-0.137***	-0.166***	-0.089**
	(4.85)	(-1.24)	(-3.33)	(-3.99)	(-2.13)
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	17,192	15,527	13,955	12,618	11,474
R^2	0.115	0.072	0.053	0.044	0.037