Credit-Market Sentiment and the Business Cycle

David López-Salido* Jeremy C. Stein† Egon Zakrajšek‡

First draft: April 2015
This draft: December 2016

Abstract

Using U.S. data from 1929 to 2015, we show that elevated credit-market sentiment in year $t-2$ is associated with a decline in economic activity in years t and $t+1$. Underlying this result is the existence of predictable mean reversion in credit-market conditions. When credit risk is aggressively priced, spreads subsequently widen. The timing of this widening is, in turn, closely tied to the onset of a contraction in economic activity. Exploring the mechanism, we find that buoyant credit-market sentiment in year $t-2$ also forecasts a change in the composition of external finance: Net debt issuance falls in year t, while net equity issuance increases, consistent with the reversal in credit-market conditions leading to an inward shift in credit supply. Unlike much of the current literature on the role of financial frictions in macroeconomics, this paper suggests that investor sentiment in credit markets can be an important driver of economic fluctuations.

JEL Classification: E32, E44, G12
Keywords: credit-market sentiment; financial stability; business cycles

We are grateful to Olivier Blanchard, Claudia Buch, Bill English, Robin Greenwood, Sam Hanson, Òscar Jordà, Larry Katz, Arvind Krishnamurthy, Hélène Rey, Andrei Shleifer, the referees, and seminar participants at numerous institutions for helpful comments. Miguel Acosta, Ibraheem Catovic, Gregory Cohen, George Gu, Shaily Patel, and Rebecca Zhang provided outstanding research assistance. The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of anyone else associated with the Federal Reserve System.

*Federal Reserve Board of Governors. Email: david.lopez-salido@frb.gov
†Harvard University and NBER. Email: jeremy_stein@harvard.edu
‡Federal Reserve Board of Governors. Email: egon.zakrajsek@frb.gov

1 Introduction

Do credit booms create risks to future macroeconomic performance? This question has spurred a large body of research, much of it undertaken in the wake of the 2008–2009 global financial crisis. Many of the formal models in this literature follow Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) and assign financial market frictions a central role in propagating and amplifying shocks to the economy. In these models, borrowers and lenders are seen as fully rational, but subject to various forms of credit limits or collateral constraints; in many cases, externalities in leverage choice are also a key part of the story. Motivated by this class of theories, much of the empirical work has focused on balance-sheet measures of leverage or credit growth, such as the growth of bank loans (Schularick and Taylor, 2012; Jordà, Schularick, and Taylor, 2013; Baron and Xiong, 2016) or the growth of household debt (Mian, Sufi, and Verner, 2016). The general pattern that emerges from this research is that rapid increases in credit outstanding presage economic downturns.

In this paper, we take a different approach to identifying credit booms and their macroeconomic consequences, one that draws on recent work in behavioral finance and on classic accounts of financial crises by Minsky (1977, 1986) and Kindleberger (1978). We hypothesize that time-variation in sentiment on the part of credit-market investors—reflecting changes in their effective risk appetite or their beliefs about default probabilities—is an important determinant of the credit cycle. This focus on investor sentiment, as opposed to financial frictions, leads us to identify credit booms not with balance-sheet measures of credit growth, but rather with proxies for the expected returns on credit assets. The premise is that a period of buoyant sentiment is one where the objective expected returns to bearing credit risk are driven down because credit is being priced aggressively. Thus in our setting, asking whether credit booms lead to adverse macroeconomic outcomes boils down to asking whether the economy performs poorly following periods when proxies for the expected returns on credit are unusually low by historical standards.

Consistent with this hypothesis, we document that variables that have previously been shown to forecast returns in the corporate bond market also have significant predictive power for economic activity. In particular, Greenwood and Hanson (2013) have shown that when corporate bond credit spreads are narrow relative to their historical norms and when the share of high-yield (or "junk") bond issuance in total corporate bond issuance is elevated, this tends to predict reduced returns to credit investors going forward. We find that this same configuration not only embodies bad news for credit investors, but also forecasts a substantial slowing of growth in real GDP, business and residential investment, durable goods consumption, and employment over the subsequent few years. Thus, buoyant credit-market sentiment today is associated with a significant weakening of a range of real economic outcomes over the business cycle.

We couch these basic findings in terms of a two-step regression specification. In the first step, we follow Greenwood and Hanson (2013) and use two-year lagged values of credit spreads and the junk share to forecast future changes in credit spreads. Our innovation is then to take the fitted values from this first-step regression, which we interpret as capturing fluctuations in credit-market sentiment, and to use them in a second-step regression to predict changes in various measures of economic and labor-market activity.

A simpler, one-step version of this approach is familiar from previous work. This work has established that near-term movements in spreads—as opposed to forecasted changes in credit spreads based on lagged valuation indicators—have substantial explanatory power for current and future economic activity.[1] Of course, results of this sort are open to a variety of causal interpretations. One possibility is that economic activity fluctuates in response to exogenous nonfinancial factors, and forward-looking credit spreads simply anticipate these changes in real activity. Our two-step results, however, weigh against this interpretation: We show that a *predictable* component of credit-spread changes that reflects not recent news about future cashflows, but rather an unwinding of past investor sentiment, still has strong explanatory power for future activity.

Interestingly, the analogous two-step results do not hold for measures of stock-market sentiment. For example, while Shiller's (2000) cyclically adjusted earnings-price ratio has been shown to forecast aggregate stock returns, we find that it has little predictive power for real activity; the same holds true for many of other stock-market predictors that have been uncovered in the literature. In this sense, the credit market is fundamentally different from the stock market, as well as of potentially greater macroeconomic significance.

In quantitative terms, our estimates using U.S. data over the period from 1929 to 2015 indicate that when our proxy for credit-market sentiment in year $t-2$ (the fitted value of the year-t change in the credit spread) moves from the 25th to the 75th percentile of its historical distribution, this change is associated with a cumulative decline in real per-capita GDP growth of about 3.2 percentage points over years t and $t+1$ and with an increase in the unemployment rate of nearly 1.5 percentage points over the same period. However, these estimates are influenced by the extreme economic events of the 1930s. Using a post-war sample from 1952 to 2015 that yields somewhat smaller and more stable estimates—which we take as our more-conservative baseline in much of the paper—the corresponding effects on output and unemployment are 1.2 percentage points and 0.8 percentage points, respectively.

While our two-step econometric methodology mechanically resembles an instrumental-variables (IV) approach, we do not make any strong identification claims based on these results. This is because we do not think that the sentiment variables used in our first-step regression would plausibly satisfy the exclusion restriction required for an IV estimation strategy. Ultimately, the hypothesis that we are interested in is this: Buoyant credit-market sentiment at time $t-2$ leads to a reversal in credit spreads at time t, and this reversal is associated with a reduction in the availability of credit, which, in turn, causes a contraction in economic activity. Now consider an alternative story along the lines of Rognlie, Shleifer, and Simsek (2016): General investor optimism at time $t-2$ leads to over-investment in some sectors, and it is this inefficient investment—for example, an excess supply

[1] There is a long tradition in macroeconomics of using credit spreads to forecast economic activity. Bernanke (1990) and Friedman and Kuttner (1992, 1993a,b, 1998) examine the predictive power of spreads between rates on short-term commercial paper and rates on Treasury bills. Gertler and Lown (1999), Gilchrist, Yankov, and Zakrajšek (2009), and Gilchrist and Zakrajšek (2012), in contrast, emphasize the predictive content of spreads on long-term corporate bonds. See Stock and Watson (2003) for an overview of the literature that uses asset prices to forecast economic activity.

of housing units or of capital in certain industries—rather than anything having to do with credit supply that sets the stage for a downturn beginning at time t.[2] In other words, our sentiment proxies may be predicting something not about future credit supply, but rather about future credit demand. There is nothing in our baseline results that weighs decisively against this alternative hypothesis.

One way to make further progress on identifying a credit supply channel is to flesh out its further implications for aspects of firm financing activity, as opposed to just real-side behavior. If a credit supply channel is at work, we should see additional patterns that are not predicted by any obvious version of the inefficient-investment hypothesis: Our sentiment proxies at time $t-2$ should not only predict changes in real activity beginning at time t, but also a change in the composition of external finance. More precisely, to the extent that credit supply has contracted, we should see a decrease in net debt issuance relative to net equity issuance.[3] And indeed, this is exactly what we find.

In addition, if fluctuations in credit-market sentiment are causing movements in the supply of credit, our methodology should uncover a stronger response of investment for firms with lower credit ratings. This is because insofar as there is variation in aggregate credit-market sentiment, the higher leverage of these firms implies a higher beta with respect to the credit-sentiment factor. Simply put, price-to-fundamentals falls by more for Caa-rated issuers than for Aa-rated issuers when market-wide sentiment deteriorates; accordingly, there should be a greater impact on their perceived cost of borrowing and therefore on their investment behavior. Again, the evidence is broadly consistent with these predictions.

The remainder of the paper is organized as follows. We begin in Section 2 by providing a conceptual framing for our empirical approach. To do so, we contrast the macroeconomic implications of models of credit booms based entirely on financial frictions with those that also incorporate a role for behavioral factors such as extrapolative beliefs. In Section 3, we establish the basic results described above, focusing on both the full 1929–2015 period and the less outlier-prone sample of 1952 to 2015. In Section 4, we attempt to zero in on the economic mechanisms, specifically on the role of sentiment-induced shifts in the supply of credit. Doing so requires a variety of further micro data that only become available more recently, so some of the results in this section come from shorter sample periods. Section 5 concludes.

2 Theories of the Credit Cycle

In this section, we discuss different theories, which suggest that credit booms might lead to recessions or financial crises. We divide these theories into two categories: Those based on financial frictions and those that feature an independent role for investor beliefs, or sentiment.

[2] In Rognlie, Shleifer, and Simsek (2016), an overbuilding of housing creates an excess supply that must be worked off. If the zero lower bound on nominal interest rates does not bind, this adjustment involves a decline in interest rates, and a reallocation of resources from housing to other sectors, but no recession. However, in the presence of a binding zero lower bound, the equilibrating mechanism is stymied, and the result is a Keynesian slump.

[3] This empirical strategy is similar in spirit to Kashyap, Stein, and Wilcox (1993).

2.1 Theories Based on Financial Frictions

There is a long tradition in macroeconomics of using models with financial frictions to study aggregate fluctuations, with an influential early example being Fisher's (1933) discussion of debt-deflation dynamics during the Great Depression. Modern formal treatments begin with Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) and tend to share certain core ingredients. First, while all agents have rational expectations, those with attractive investment or consumption opportunities face agency costs of raising external equity or, in some cases, are precluded from using outside equity altogether. As a result, debt contracts are the primary mode of external finance. However, there are frictions in the debt market as well, with the ability to borrow being constrained, by either an exogenous debt limit or some function of endogenous borrower net worth or collateral value.

Taken together, these ingredients generate amplification and propagation effects: When a negative shock hits the economy, firms and households that have levered up to finance past investment and consumption find their net worth impaired. Given frictions in the debt market, this forces them to reduce borrowing and to cut back on future investment and consumption. The associated reduction in aggregate demand in turn sets the stage for further declines in economic activity, leading to another round of reductions in net worth and collateral values, and so on.

Several recent papers extend this approach to deliver results that are particularly relevant in light of the 2008–2009 financial crisis. Brunnermeier and Sannikov (2014) show that the amplification effects described above may be highly non-linear, so that the economy's response to a large external shock can be much stronger than its response to a smaller shock. Hall (2011), Eggertsson and Krugman (2012), and Guerrieri and Lorenzoni (2015) all argue that the resulting downturn will be deeper and more protracted when the zero lower bound (ZLB) on interest rates interferes with the equilibrating process set in motion by a shock that requires agents to reduce their leverage.

Given that agents in these models are rational, one question that arises is why they would take on so much debt in the first place if doing so makes the economy so fragile. The general answer proposed in the literature is that there are externalities in leverage choice: Individual agents do not fully internalize the vulnerabilities that their own borrowing decisions impose on the aggregate economy, and so they over-borrow from the perspective of a social planner. These externalities can be rooted in either fire-sale effects (Shleifer and Vishny, 1992; Lorenzoni, 2008; Stein, 2012; Dávila and Korinek, 2016) or in aggregate demand spillovers in the presence of a binding ZLB (Farhi and Werning, 2016; Korinek and Simsek, 2016).

In sum, models in the financial-frictions genre can provide a compelling account of both why economies with highly levered firms, households, or intermediaries can be vulnerable to exogenous shocks, and why the decentralized decisions of these actors can lead to high leverage ex ante, in spite of its potential costs. Moreover, with their emphasis on leverage as a state variable that captures the fragility of the economy, they provide grounding for empirical work that uses balance-sheet measures of leverage to predict economic downturns (see Schularick and Taylor, 2012; Jordà, Schularick, and Taylor, 2013; Mian, Sufi, and Verner, 2016). Finally, given the assumption of rational expectations and the focus on classical externalities—as opposed to mistaken beliefs—in generating excessive leverage, these models are also a natural starting point for the normative analysis of macroprudential regulation (see Farhi and Werning, 2016; Korinek and Simsek, 2016).

However, because they are fundamentally theories of amplification and propagation and rely on exogenous shocks to set the system in motion, this class of models typically has less to say about *when* and *how* a credit-driven downturn gets triggered. Relatedly, they are for the most part silent on the *duration* of the credit cycle. For example, if significant negative shocks only arrive infrequently, an econometrician observing that the economy is in a fragile high-leverage state—but having no further information about the probability of the exogenous shock hitting—might have to wait a long time on average before seeing the predicted downturn.

2.2 Behavioral Theories

An alternative approach to studying credit booms and their consequences builds on the narratives of Minsky (1977, 1986) and Kindleberger (1978) and on the large literature in behavioral finance, which analyzes the dynamics of asset prices when some investors update their beliefs in a not-fully-rational manner.[4] Two recent contributions in this vein are Bordalo, Gennaioli, and Shleifer (2016), hereafter BGS, and Greenwood, Hanson, and Jin (2016), or GHJ. These papers can be thought of as trying to explain three sentiment-related aspects of the credit cycle: (1) why investors sometimes become overoptimistic, thereby driving credit spreads to unduly low levels; (2) what causes the optimism to reverse endogenously, leading to a subsequent tightening of credit conditions; and (3) the associated macroeconomic dynamics.

In BGS, credit cycles arise from a particular psychological model of belief formation, which the authors dub "diagnostic expectations," a process that is inherently extrapolative in nature. Specifically, expectations about future credit defaults are overly influenced by the current state of the economy, so that when there is good news about fundamentals, investors become too optimistic, credit spreads narrow, the quantity of credit expands, and real activity picks up. A key point is that this mechanism leads to *endogenous reversals of sentiment* because following periods of narrow spreads, further economic news will, on average, tend to be disappointing relative to optimistic expectations. This disappointment leads to a widening of spreads that is predictable from the perspective of an econometrician, as well as to a decline in economic activity induced by the contraction in the supply of credit. These implications are summarized in Proposition 5 of BGS: "Suppose ... at $t-1$ credit spreads are too low due to recent good news. Then controlling for fundamentals at $t-1$, credit spreads predictably rise at t. [And] controlling for fundamentals at $t-1$,

[4] Early work in this area tries to explain the joint presence of over- and under-reaction patterns in asset prices to economic news; see, for example, Cutler, Poterba, and Summers (1990); Barberis, Shleifer, and Vishny (1998); and Hong and Stein (1999). Particularly relevant for the present purposes are recent papers that emphasize extrapolation as a source of mistaken beliefs; these studies include Greenwood and Shleifer (2014) and Koijen, Schmeling, and Vrugt (2015).

there is a predictable drop in aggregate investment at t and in aggregate production at $t+1$."

Our basic two-step empirical specification closely mirrors this proposition. The first step, which replicates Greenwood and Hanson (2013), uses lagged information on credit spreads and high-yield bond issuance to forecast future changes in spreads. The second step asks whether predicted widenings in spreads are also associated with declines in investment and real activity.

In the models of BGS and GHJ, time-varying credit-market sentiment arises from the extrapolative beliefs of investors. An alternative view, closer in spirit to the financial-frictions literature, holds that while mistaken beliefs may be important, they are not the whole story (Stein, 2013). Rather, financial constraints and agency problems at the intermediary level may also be part of the mechanism driving time-variation in expected returns to credit investors.

One strand of this literature highlights the role of intermediaries' balance sheets. Adrian, Etula, and Muir (2014) argue that in a world of segmented markets, the wealth of broker-dealers is the stochastic discount factor that prices risky assets—when broker-dealer balance sheets are strong and the marginal value of their wealth is low, expected returns on risky assets are low as well. He and Krishnamurthy (2013) build an asset pricing model with an intermediary sector that has similar implications.[5] A complementary line of work focuses on an agency problem between intermediaries and their shareholders and claims that the problem is intensified when the level of interest rates is low because this makes intermediaries more likely to "reach for yield"—that is, to accept lower premiums for bearing duration and credit risk—at such times.[6]

Although it may be difficult to separate the two classes of theories entirely, one useful piece of evidence comes from the expectations embodied in survey data. BGS examine forecasts of future credit spreads from the Blue Chip survey. They find that when current credit spreads are low, the survey respondents systematically *under-forecast future credit spreads* and conversely when credit spreads are high—in other words, their forecast errors are biased. This evidence is consistent with the presence of mistaken beliefs, but it is harder to reconcile with stories based on agency problems at the intermediary level because in these stories agents knowingly accept lower expected returns at certain points in the cycle.[7] Of course, this does not rule out a place for the agency-based models, but it does seem to rule in a role for those based on extrapolative beliefs.

Finally, one feature that is not always explicit in behavioral models, but which is important for our empirical work, is a clear separation between sentiment in the credit market and sentiment in the stock market. As we show below, these two concepts are sharply distinct in the data: Those variables that have the most predictive power for expected credit returns have little to say about expected equity returns and vice-versa. This type of segmentation in sentiment might at first seem surprising—if investors are too optimistic about the economy's growth prospects, one might think that they would overvalue both debt and equity claims, leading to sentiment that is highly

[5] See also Brunnermeier and Pedersen (2009); Danielsson, Shin, and Zigrand (2011); and Adrian and Boyarchenko (2013) for related work.

[6] See, for example, Rajan (2006); Borio and Zhu (2012); Jiménez, Ongena, Peydró, and Saurina (2014); Hanson and Stein (2015); Gertler and Karadi (2015); and Lian, Ma, and Wang (2016).

[7] In a similar vein, GHJ find that lagged corporate bond default rates have substantial explanatory power for current credit spreads, again suggesting a role for extrapolation in driving investors' beliefs.

correlated across markets. However, other beliefs-based models can rationalize a greater degree of segmentation in sentiment, to the extent that the mistakes that investors make are not only about expected cashflows, but also about the probability of lower-tail outcomes.[8] Segmentation can also arise from a variety of institutional and agency frictions, such as regulations that inhibit certain classes of debt-market intermediaries like banks and insurance companies from also being active in the stock market.

2.3 Towards an Integrated View

We have thus far discussed the financial-frictions and sentiment-based theories of credit cycles separately, both because they are logically distinct and because the latter are necessary to motivate our empirical approach. However, it seems likely that the mechanisms in the two classes of theories would be complementary, and certainly none of the findings that we present below cut in any way against the frictions-based models. To the contrary, we make some effort to explore the complementarities explicitly.[9]

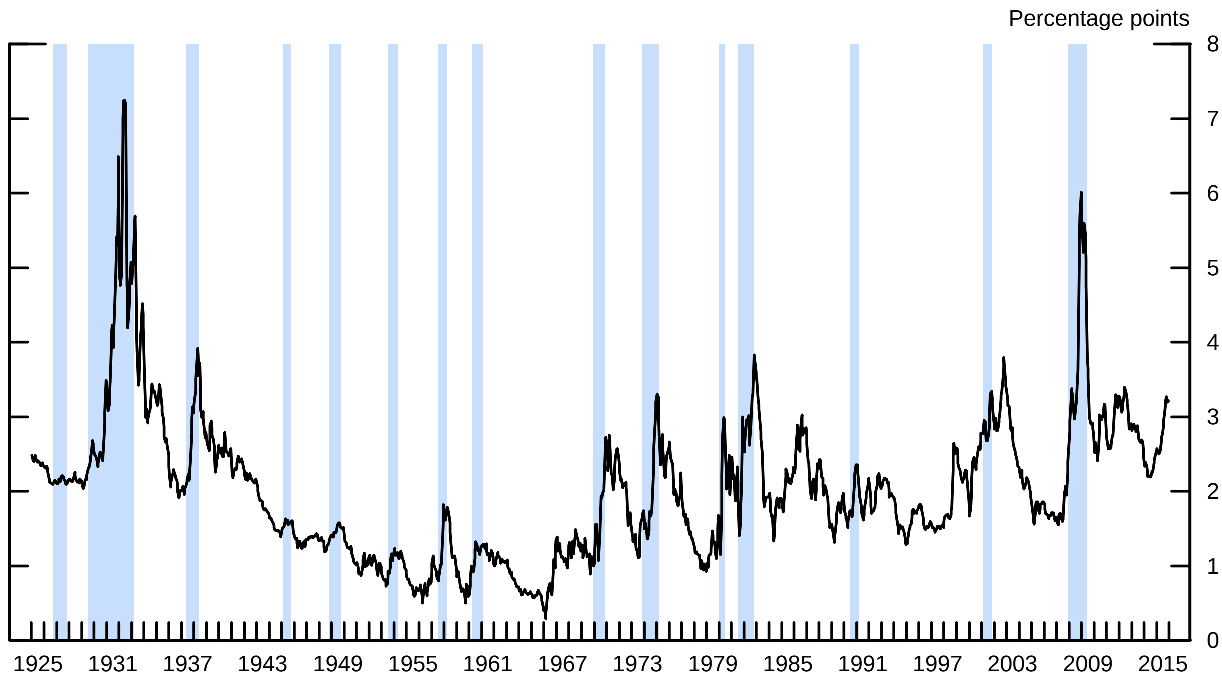
One way to understand how the two classes of theories fit together is to recall that the frictions-based models are well-suited to explaining why the economy can find itself in a fragile highly-leveraged state, but they typically rely on a black-box exogenous shock to actually kick off a downturn. That is, they are effectively *models of vulnerabilities, not triggers*. Conversely, the sentiment-based approach, which emphasizes the endogenous unwinding of over-optimistic beliefs, comes closer to providing a theory of triggers. This interplay between leverage and mispricing is central to Minsky (1977, 1986), and it is also invoked in some of the more recent theoretical work in the frictions genre. In Eggertsson and Krugman (2012), for example, the exogenous shock to the economy is an unanticipated tightening of borrowing limits. To motivate this reduced-form assumption, they say: "[W]e can represent a Minsky moment as a fall in the debt limit ..., which we can think of as corresponding to a sudden realization that assets were overvalued." (p. 1475). This logic suggests that information on the extent of overvaluation, and the anticipated path of mean reversion, should add to the explanatory power of the frictions-based theories.

These observations carry two messages for empirical work. First, while both balance-sheet measures and sentiment measures may independently have predictive power for economic outcomes, one should not necessarily think of them as operating at similar horizons. As previously noted,

[8] In Gennaioli, Shleifer, and Vishny (2012), infinitely risk-averse investors neglect the existence of a low-probability disaster state, which matters relatively more for the pricing of debt than of equity. The disagreement framework of Geanokoplos (2009) and Simsek (2013) can also generate a divergence between the pricing of debt and equity, depending on whether investors disagree more about the lower or upper tail of outcomes. Relatedly, one way to model segmented mispricing in the classic debt-pricing framework of Merton (1974) is to posit that investors have mistaken beliefs not only about the expected returns on assets, but also their volatility. The former type of mistake induces a positive correlation in the pricing of debt and equity, but the latter pushes them in opposite directions.

[9] On the theoretical front, GHJ study the interplay of endogenous sentiment and frictions. In their model, beliefs about future defaults are extrapolated based not on the state of the real economy—as in BGS—but on past defaults. And realized defaults depend in part on credit supply and, by extension, on investor beliefs. This creates a richer dynamic structure: As investors become more pessimistic, credit supply tightens, making it harder for firms to roll over their debt, which leads to more defaults and a further deepening of pessimism.

Figure 1 – Baa-Treasury Credit Spread



Note: The solid line depicts the spread between the yield on Moody's seasoned Baa-rated industrial bonds and the 10-year Treasury yield. The shaded vertical bars denote the NBER-dated recessions.

absent any information on the conditional likelihood of a triggering event, a high-leverage regime might be expected to persist for a long time before there are adverse macroeconomic consequences. By contrast, in the presence of high leverage—and depending on the dynamics of belief revisions—once asset prices are significantly elevated, an economic correction may be closer at hand.

Second, the vulnerabilities-plus-triggers framing suggests an interactive specification. In other words, the predictive power of elevated credit-market sentiment should be stronger in the presence of high debt levels. Although it is not our main focus, we explore several specifications along these lines and find some evidence in the U.S. data that is consistent with this hypothesis; Krishnamurthy and Muir (2016) follow a similar logic employing country-level panel data.

3 Credit-Market Sentiment and the Macroeconomy

3.1 Measuring Credit-Market Sentiment

Throughout the paper, we work with a simple measure of credit spreads, namely the spread between yields on seasoned long-term Baa-rated industrial bonds and yields on comparable-maturity Treasury securities. (Details on data sources and on the construction of all variables used in the analysis are in the Online Appendix A.) Figure 1 plots this series over the period from 1925 to 2015. Clearly evident in the figure is the countercyclical nature of credit spreads, with spreads generally widening noticeably in advance of and during economic downturns.

When we talk about credit-market sentiment, we mean more precisely the expected return to bearing credit risk based on a particular forecasting model. Thus, when we say that sentiment is elevated, this is equivalent to saying that the expected return to bearing credit risk is low. In an effort to generate a sentiment proxy that we can use over a long sample period, we follow Greenwood and Hanson (2013) (GH hereafter). They are interested in capturing the expected excess returns associated with bearing credit risk, and they find that a simple linear regression with two forecasting variables—the level of credit spreads and the junk-bond share as of year $t-2$—has substantial predictive power for year-t returns on corporate bonds compared with those on Treasury securities. To operationalize this concept, we forecast in our baseline specifications annual changes in the Baa-Treasury spread using these two GH-nominated variables as our primary measures of credit-market sentiment.

In addition to these two forecasting variables, we add in an alternative specification the level of the term spread (also as of year $t-2$), defined as the difference between the yields on long- and short-term Treasury securities, as an additional proxy for credit-market sentiment. As shown by GH, and as we verify, it turns out that the Treasury term spread is an incrementally strong predictor of future credit returns: When the term spread is low, credit spreads are predicted to widen. One might hypothesize that this pattern arises because both term and credit spreads are sometimes compressed by the same sorts of reaching-for-yield pressures and hence have something of a common factor structure. In a world in which any one proxy for expected returns is noisy—for example, credit spreads reflect not only expected returns to bearing credit risk but also time-varying default probabilities—an additional proxy that also captures some piece of the underlying common factor may be helpful in forecasting excess credit returns.

Finally, over a shorter sample period running from 1973 to 2015, we also experiment with one other sentiment indicator: the excess bond premium (EBP) of Gilchrist and Zakrajšek (2012).[10] The EBP is effectively a measure of credit spreads net of an estimate of default risk and hence has a natural interpretation in terms of expected credit returns. Reassuringly, we obtain very similar results—in both our first- and second-step regressions—with the EBP and with the sentiment proxies proposed by Greenwood and Hanson (2013).

Although it is not the main focus of the paper, we also examine the impact of stock-market sentiment on economic activity. We proceed analogously to the case of credit markets, defining sentiment as the fitted value from a return-forecasting model. The literature on forecasting aggregate stock returns is vast, so in our baseline specifications we confine ourselves to one of the most familiar predictor variables: Shiller's (2000) cyclically adjusted price-earnings ratio. However, we have also experimented with a number of other predictors, including the dividend-price ratio (Fama and French, 1988; Cochrane, 2007), the equity share in total external finance (Baker and Wurgler, 2000), and the consumption-wealth ratio (Lettau and Ludvigson, 2001), with similar results.

[10] The EBP is only available over this shorter sample period because it is constructed using firm-level data.

Table 1 – Forecasting Economic Growth with Credit Spreads and Stock Prices

	Dependent Variable: Δy_t		
Regressors	(1)	(2)	(3)
Δs_{t-1}	-1.997^{***}	.	-2.061^{**}
	(0.746)		(0.847)
r^{SP}_{t-1}	.	0.081^{***}	0.029
		(0.029)	(0.036)
Δy_{t-1}	0.479^{***}	0.475^{***}	0.464^{***}
	(0.080)	(0.082)	(0.079)
$\Delta i^{(3m)}_{t-1}$	.	.	-0.217
			(0.198)
$\Delta i^{(10y)}_{t-1}$	.	.	-0.719^{**}
			(0.346)
π_{t-1}	.	.	0.069
			(0.050)
$\bar{R}^2$	0.425	0.389	0.450
Standardized effect on Δy_t [a]			
Δs_{t-1}	-0.369	.	-0.380
r^{SP}_{t-1}	.	0.319	0.114

Note: Sample period: annual data from 1929 to 2015. The dependent variable is Δy_t, the log-difference of real GDP per capita from year $t-1$ to year t. Regressors: Δs_t = change in the Baa-Treasury spread; r^{SP}_t = S&P 500 total (log) return; $\Delta i^{(3m)}_t$ = change in the 3-month Treasury yield; $\Delta i^{(10y)}_t$ = change in the 10-year Treasury yield; and π_t = CPI inflation. All specifications include a constant (not reported) and are estimated by OLS. Heteroskedasticity- and autocorrelation-consistent asymptotic standard errors reported in parentheses are computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994): * $p < .10$; ** $p < .05$; and *** $p < .01$.

[a] The standardized estimate of the coefficient associated with the specified financial indicator. StdDev(Δy_t) = 4.82 percent; StdDev(Δs_t) = 86 basis points; and StdDev(r^{SP}_t) = 18.2 percent.

3.2 Forecasting Economic Growth with Credit Spreads and Stock Prices

As a preliminary exploration of the data, Table 1 presents results from a series of OLS regressions, in which we attempt to forecast Δy_t, the log-difference of real GDP per capita over the course of year t, using either changes in credit spreads or stock returns over the prior year $t-1$. More formally, we estimate variants of the following standard forecasting regression:

$$\Delta y_t = \beta_1 \Delta s_{t-1} + \beta_2 r^{SP}_{t-1} + \boldsymbol{\gamma}' \mathbf{x}_{t-1} + \epsilon_t, \tag{1}$$

where Δs_{t-1} is the change in the Moody's Baa-Treasury credit spread over year $t-1$, r^{SP}_{t-1} is the (total) log return on the S&P 500 over year $t-1$, and $\mathbf{x}_{t-1}$ is a vector of controls that includes the log-difference of real GDP per capita from year $t-2$ to $t-1$, the CPI inflation rate in year $t-1$, and the changes in both the 3-month and 10-year Treasury yields from year $t-2$ to $t-1$. The sample period runs from 1929 through 2015.

In column (1) of the table, the explanatory variable of interest is Δs_{t-1}. As can be seen, changes in credit spreads have substantial forecasting power for future economic growth: A one standard deviation increase in credit spreads—86 basis points—is associated with a step-down in real GDP growth per capita of 0.37 standard deviations, or about 1.8 percentage points. In column (2), we repeat the exercise, replacing Δs_{t-1} with r^{SP}_{t-1}. In this simple exercise, the forecasting power of the stock market is roughly similar to that of the corporate bond market: A one standard deviation increase in the broad stock market—about 18 percent—predicts an increase in the next year's real GDP growth per capita of 0.32 standard deviations.[11] In column (3), we let Δs_{t-1} and r^{SP}_{t-1} enter the regression together and also add all of the other controls. In this case, the coefficient on Δs_{t-1} is virtually unchanged from its value in column (1), while the coefficient on r^{SP}_{t-1} declines substantially. Thus the simple predictive power of credit spreads for real activity appears to be somewhat more robust than that of stock returns.

3.3 Financial-Market Sentiment and Economic Activity: 1929–2015

Of course, there is good reason to think that the above predictive relationships may not be causal. Economic activity may move around for a variety of exogenous nonfinancial reasons, and forward-looking credit spreads and stock prices may simply anticipate these changes. In this section, we try to isolate the component of asset price movements that comes from an unwinding of past investor sentiment, as opposed to changes in expectations of future cashflows.

As described earlier, we do so by means of a two-step regression specification. In the first step, we use a set of valuation indicators to forecast future changes in credit spreads and stock returns. We then take the fitted values from the first step, which we interpret as capturing fluctuations in financial-market sentiment, and use them in a second-step regression to predict changes in various measures of economic activity. Formally, our econometric method consists of the following set of equations:

$$\Delta s_t = \boldsymbol{\theta}_1' \mathbf{z}_{1,t-2} + \nu_{1t}; \tag{2}$$

$$r^{SP}_t = \boldsymbol{\theta}_2' \mathbf{z}_{2,t-2} + \nu_{2t}; \tag{3}$$

$$\Delta y_{t+h} = \beta_1 \Delta\hat{s}_t + \beta_2 \hat{r}^{SP}_t + \boldsymbol{\gamma}'\mathbf{x}_{t-1} + \epsilon_{t+h}; \quad (h \geq 0), \tag{4}$$

where $\Delta\hat{s}_t = \hat{\boldsymbol{\theta}}_1' \mathbf{z}_{1,t-2}$ and $\hat{r}^{SP}_t = \hat{\boldsymbol{\theta}}_2' \mathbf{z}_{2,t-2}$. The first two forecasting regressions project current changes in credit spreads and stock returns on their respective two-year lagged valuation indicators, denoted by $\mathbf{z}_{1,t-2}$ and $\mathbf{z}_{2,t-2}$. The third equation estimates the effect that variation in these expected returns has on current and future economic activity. To take into account the generated-regressor nature of the expected returns, the above system of equations is estimated jointly by nonlinear least squares (NLLS).[12]

[11] Research documenting the predictive power of stock returns for future economic activity can be traced back to Fama (1981) and Fischer and Merton (1984).

[12] Statistical inference of the parameters of interest is based on a heteroskedasticity- and autocorrelation-consistent asymptotic covariance matrix computed according to Newey and West (1987), utilizing the automatic lag selection method of Newey and West (1994).

Table 2 – Two-Step Results: Financial-Market Sentiment and Economic Growth

	Dependent Variable: Δy_t			
Regressors	(1)	(2)	(3)	(4)
$\Delta \hat{s}_t$	-4.800^{***}	.	-4.409^{***}	-5.389^{***}
	(1.134)		(1.053)	(1.900)
$\hat{r}_t^{SP}$	.	0.145^{**}	0.069	.
		(0.057)	(0.050)	
Δy_{t-1}	0.598^{***}	0.532^{***}	0.592^{***}	0.579^{***}
	(0.099)	(0.077)	(0.096)	(0.069)
$\Delta i_{t-1}^{(3m)}$	.	.	.	0.131
				(0.239)
$\Delta i_{t-1}^{(10y)}$	.	.	.	-0.510
				(0.410)
π_{t-1}	.	.	.	0.104
				(0.163)
R^2	0.379	0.332	0.386	0.391
	Auxiliary Regressions			
	Δs_t	r_t^{SP}		
$\ln \text{HYS}_{t-2}$	0.095^{***}	.		
	(0.024)			
s_{t-2}	-0.248^{***}	.		
	(0.042)			
$\ln[P/E10]_{t-2}$	.	-0.134^{***}		
		(0.036)		
R^2	0.100	0.086		

Note: Sample period: annual data from 1929 to 2015. The dependent variable is Δy_t, the log-difference of real GDP per capita from year $t-1$ to year t. Regressors: $\Delta \hat{s}_t$ = predicted change in the Baa-Treasury spread; $\hat{r}_t^{SP}$ = predicted S&P 500 total (log) return; $\Delta i_t^{(3m)}$ = change in the 3-month Treasury yield; $\Delta i_t^{(10y)}$ = change in the 10-year Treasury yield; and π_t = CPI inflation. In the auxiliary forecasting equations: HYS_t = fraction of debt that is rated as high yield (Greenwood and Hanson, 2013, the coefficient is multiplied by 100); and $[P/E10]_t$ = cyclically adjusted P/E ratio for the S&P 500 (Shiller, 2000). All specifications include a constant (not reported) and are estimated jointly with their auxiliary forecasting equation(s) by NLLS. Heteroskedasticity- and autocorrelation-consistent asymptotic standard errors reported in parentheses are computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994): * $p < .10$; ** $p < .05$; and *** $p < .01$.

Table 2 presents our full-sample (1929–2015) results, corresponding to the forecast horizon $h = 0$. Consider first column (1) and begin by focusing on the lower panel of the table. Here is the first-step regression, in which we predict Δs_t with two variables: (1) the log of HYS_{t-2}, where HYS_{t-2} denotes high-yield bond issuance in year $t-2$, expressed as a share of total bond issuance in the nonfinancial corporate sector; and (2) s_{t-2}, the level of the Baa-Treasury credit spread at the end of year $t-2$. Again, this approach to forecasting Δs_t is taken directly from Greenwood and Hanson (2013).[13] As can be seen, the log of HYS_{t-2} enters with a significantly

[13]We also follow GH by defining HYS_{t-2} based on the fraction of nonfinancial gross bond issuance in a given year that is rated by Moody's as below investment grade.

positive coefficient, implying that an elevated level of the high-yield share in year $t-2$ predicts a subsequent widening of credit spreads in year t. And s_{t-2} enters with a negative coefficient, which implies that when the credit spread is low in year $t-2$, it is expected to mean revert over the course of year t. Notably, the first-step regression with these two predictors yields an R^2 of 0.10, so our valuation measures are reasonably powerful in predicting future movements in credit spreads.[14] This is all closely consistent with the results in Greenwood and Hanson (2013).

Turning to the upper panel of Table 2, column (1) shows that this approach yields an estimate of the impact of $\Delta\hat{s}_t$ on Δy_t that is strongly statistically significant. We interpret this as saying that the component of credit-spread changes that is driven by a reversal of prior sentiment has a significant impact on economic activity. This finding, which closely mirrors the theoretical prediction in Bordalo, Gennaioli, and Shleifer (2016), is our central result.

In column (2) of Table 2, we replace $\Delta\hat{s}_t$ with the fitted stock-market return, $\hat{r}_t^{SP}$, and, following Shiller (2000), use the log of the cyclically adjusted price-earnings ratio as of $t-2$ ($\ln[P/E10]_{t-2}$) as the predictor for r_t^{SP}. In this specification, the coefficient on the expected stock market return is also significant. However, when we run a horse race in column (3) by including the fitted values of both Δs_t and r_t^{SP} in the second-step regression simultaneously, the fitted change in the credit spread is the clear winner: Its coefficient is almost identical to that from column (1), while the coefficient on the fitted stock market return is close to zero and statistically insignificant.

In Tables B-1 and B-2 of the Online Appendix B, we show that these qualitative findings are reinforced when we look at a variety of other predictors of stock returns, including the dividend-price ratio (Fama and French, 1988; Cochrane, 2007), the new equity share in total external finance (Baker and Wurgler, 2000), and the consumption-wealth ratio (Lettau and Ludvigson, 2001). In each case, the fitted values of stock returns that are generated using these predictors do not have significant explanatory power for Δy_t when entered in horse-race specifications like those of column (3). More strikingly—and unlike what we obtained with the cyclically adjusted price-earnings ratio as a predictor—they also fail to work even when entered by themselves, as in column (2).[15]

Thus, overall, specifications such as those in Table 2 point to a sharp divergence between the credit market and the stock market. Only fitted changes in credit spreads—that is, proxies for credit-market sentiment—predict output growth robustly when we take a two-step regression approach.[16] Moreover, as shown in column (4), the explanatory power of credit-market sentiment for economic growth remains essentially unchanged when we include standard macroeconomic controls in the second-step regression. The striking difference in the information content between our

[14] It is also worth noting that in addition to their statistical significance, both of these valuation measures have an economically meaningful impact on future changes in credit spreads; for example, the standardized coefficients associated with $\ln \mathrm{HYS}_{t-2}$ and s_{t-2} in the first-step regression are 0.18 and -0.30, respectively.

[15] As a robustness check, we also experimented with using different lags for the various predictors of stock returns (all the way from one year to five years). These variations did not help to make stock-market sentiment—that is, the fitted value of stock returns—any more useful in explaining output growth.

[16] The divergence cannot be explained based on the first-step forecasting regressions for stock returns being less powerful than those for changes in credit spreads. As can be seen by comparing the bottom panel of Table 2, these first-step regressions have similar R^2 values. Thus, the problem is not that stock returns cannot be predicted; rather, it is that the variables that predict stock returns have little incremental forecasting power for real activity.

proxies for credit- and stock-market sentiment would seem to suggest that any forecasting power the stock market has for the real economy arises primarily from its role as a passive predictor, rather than from any causal impact of stock-market sentiment. By contrast, the results in Table 2 leave open—but do not decisively establish—the possibility that the fluctuations in credit-market sentiment play a more directly causal role with respect to real activity.

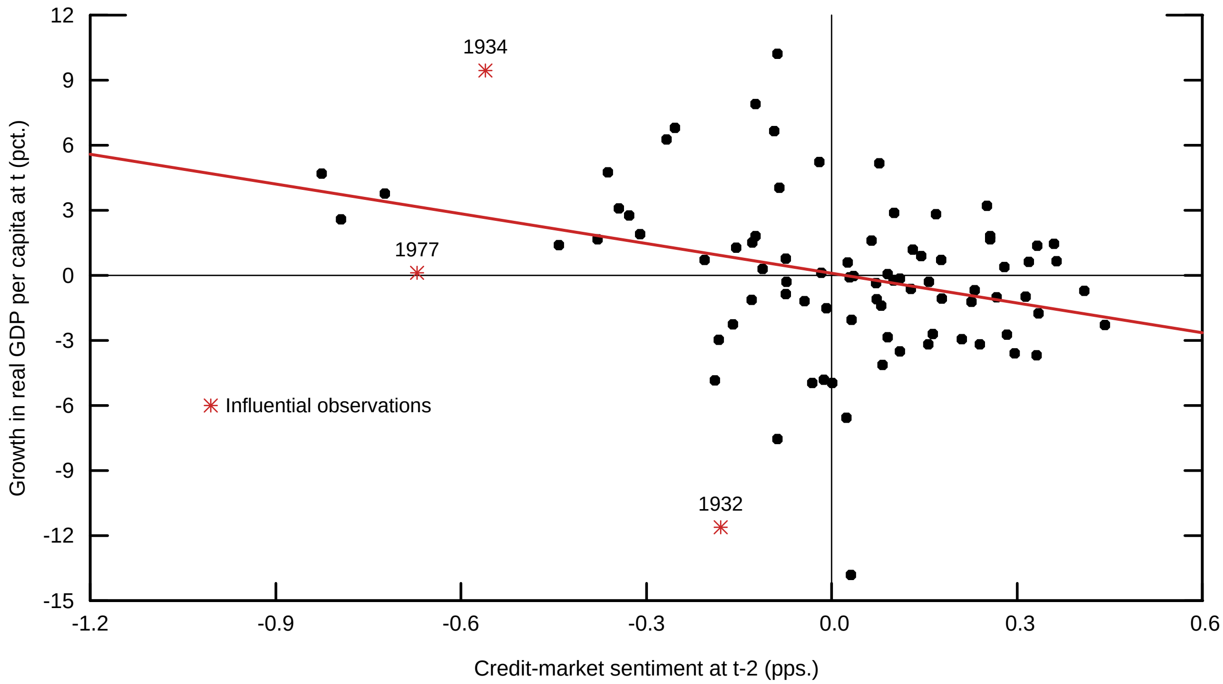
Implicit in this discussion is the premise that credit-market sentiment and stock-market sentiment are logically distinct constructs, that is, the two markets are segmented to some extent. As noted in Section 2, this form of segmentation can arise in a variety of theoretical models, but there are other benchmark settings where it does not. Indeed, one might have a priori expected the two forms of sentiment to move closely together, on the notion that generalized optimism about asset valuations would lead both debt and equity prices to increase together. However, in the data the separation is quite clear. We reinforce this point in Table B-3 of Appendix B by running augmented versions of the first-step regressions in the lower panel of Table 2, in which all the predictors of both stock returns and changes in credit spreads are entered simultaneously. It turns out that the variables that are useful for forecasting changes in credit spreads have essentially no predictive power for equity-market returns and vice-versa. In this sense, the two types of sentiment can be said to be empirically distinct.

3.4 Outliers and Subsample Stability

One might wonder to what extent the results in Table 2 are driven by a small number of disproportionately influential observations, for example, from the Great Depression or the recent Great Recession. We investigate this issue in a number of ways. To begin, Figure 2 provides a graphical illustration of the results in column (1) of Table 2. For each year in our full-sample period, we plot the value of real GDP growth per capita against the fitted value $\Delta\hat{s}_t$ from our first-step forecasting regression, with both variables in the plot having been orthogonalized relative to the other covariates in the second-step model. The slope of the line in this picture thus corresponds directly to the estimate of the coefficient on $\Delta\hat{s}_t$ reported in column (1) of Table 2. We then highlight the three specific data points, which exceed the cutoffs proposed by Belsley, Kuh, and Welsch (1980) for gauging outlier influence in linear regressions; heuristically, these data points are the ones that, when individually excluded from the regression, lead to the largest changes in the point estimate of the coefficient on $\Delta\hat{s}_t$.

Two of these overly-influential observations occur in the early years of the sample, in 1932 and 1934; the remaining one is in 1977. Figure 3 provides a more detailed analysis of this phenomenon, plotting the time series of the DFBETA statistics associated with the coefficient on $\Delta\hat{s}_t$. The DFBETA statistic for any given observation measures the change (in units of standard errors) in the estimate of the coefficient when that one observation is excluded from the regression. As can be seen, much of the jumpiness in the DFBETA series occurs in the first 20 or so years of the sample period—after about 1950, the series is much more subdued. In other words, individual observations tend to be much less influential in the post-1950 era.

Figure 2 – Credit-Market Sentiment and Economic Growth, 1929–2015

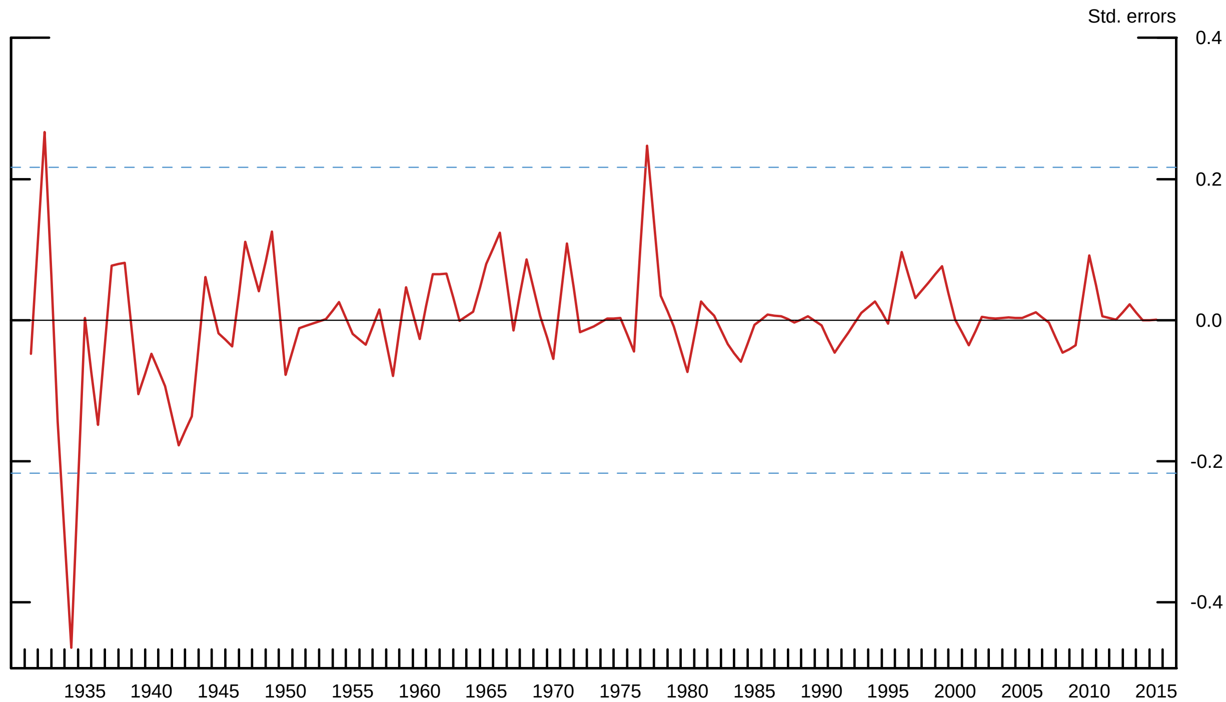


Note: The scatter plot depicts a visual representation of the relationship between credit-market sentiment in year $t-2$ and the growth in real GDP per capita from year $t-1$ to year t, implied by the specification in column (1) of Table 2. See the text and Figure 3 for the definition of influential observations

Figure 4 makes this point in a different way. We estimate the coefficient on $\Delta\hat{s}_t$ exactly as in column (1) of Table 2, but on a rolling sample with a 40-year window. We then plot the time series of these rolling estimates (the convention here is that the data point labeled "1995" reflects an estimate based on the 1955–1995 sample period). As the figure shows, while this series too was choppy as the Great Depression and World War II years moved through the sample window, the estimates have been remarkably stable over the last 30 or so years, which collectively reflect data from the 70-year post-war period. Importantly, however, these more stable recent estimates, while still strongly statistically significant, have tended to be smaller in absolute terms than the full-sample estimate (the dashed line). Thus, including the volatile early years of the sample period may tend to exaggerate the economic magnitude of our results.

With this caveat in mind, we create in Table 3 an exact counterpart of the top panel of Table 2 for two shorter subsamples. The first of these, in the upper panel of the table, covers the period 1952 to 2015, thereby excluding the portion of the sample that contains the most influential observations. The latter, in the lower panel, covers the period from 1952 to 2007, thereby further excluding the recent Great Recession. The results for these two subsamples are very similar: They generate estimated coefficients on $\Delta\hat{s}_t$ of -2.68 and -2.91, respectively, as compared to the full-sample estimate of -4.80. So while our full-sample findings are not simply the product of a few influential

FIGURE 3 – Influential Observations



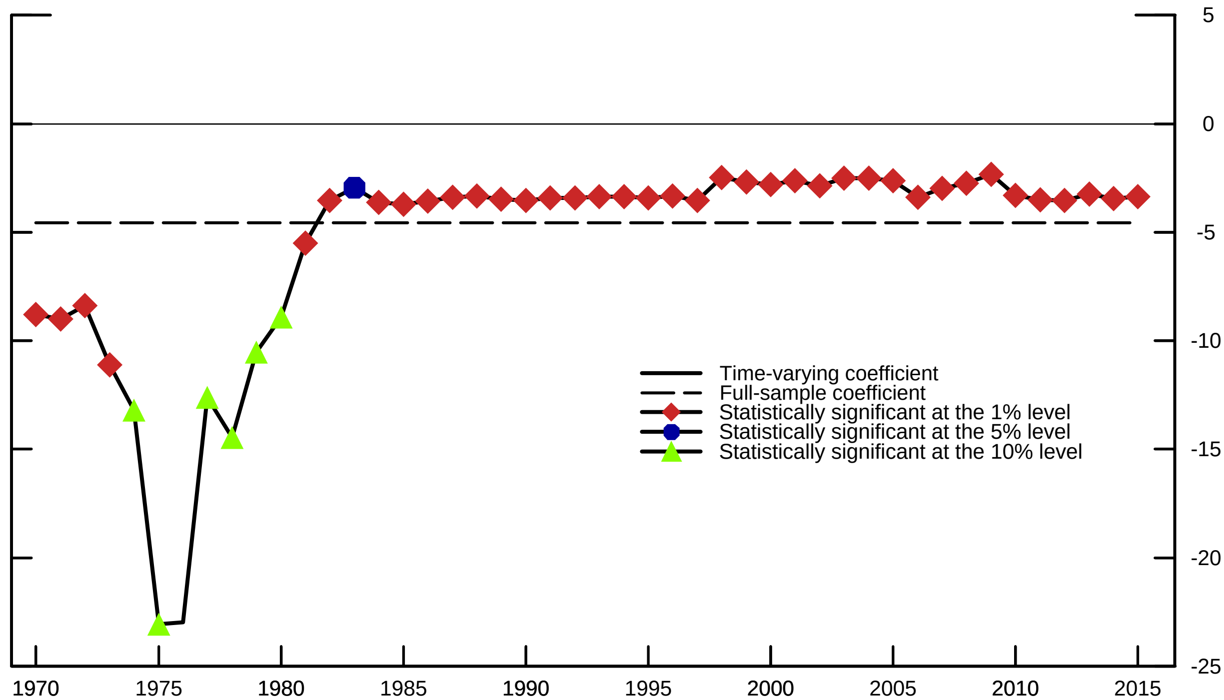
NOTE: The solid line depicts the time series of DFBETA statistics associated with the coefficient on $\Delta\hat{s}_t$ from Figure 2. The DFBETA statistic associated with observation $\tau = 1, 2 \ldots, T$ measures the change (in standard errors) in the OLS estimate of the coefficient on $\Delta\hat{s}_t$, when observation τ is excluded from the estimation. The dotted horizontal lines represent the size-adjusted cutoffs ($\pm 2/\sqrt{T}$), where $T = 85$ is the sample size (see Belsley, Kuh, and Welsch, 1980). The explanatory variables in the first-step auxiliary forecasting equation for Δs_t are $\ln \text{HYS}_{t-2}$ and s_{t-2} (see the text for details).

observations, it is clear that a handful of data points in the 1930s do contribute to markedly larger (in absolute value) point estimates. In light of this fact, in much of what follows we use the shorter postwar 1952–2015 period as our baseline sample. This does not change any of the qualitative patterns that we report, but when we discuss economic magnitudes, it does result in estimates that are more conservative and that likely provide a more plausible representation of the contemporary economic environment.

3.5 Different Horizons and Measures of Economic Activity

In Table 4, we extend the analysis in two directions, now focusing on the 1952–2015 sample period. First, in the top panel, we ask whether the predicted change in the credit spread impacts real GDP growth not only in that same year t, but also in the subsequent two years (that is, we consider forecast horizons $h = 1, 2$). As can be seen, the effects on real GDP growth are somewhat persistent—the coefficient is statistically significant again in year $t+1$ and then becomes insignificant

FIGURE 4 – Credit-Market Sentiment and Economic Growth: Rolling Estimates



NOTE: The solid line depicts the time-varying NLLS estimate of the coefficient associated with $\Delta\hat{s}_t$, the predicted change in the Baa-Treasury spread. The estimates are based on the rolling 40-year window regression in which the dependent variable is Δy_t, the log-difference of real GDP per capita from year $t-1$ to year t; additional explanatory variables include a constant and Δy_{t-1}. The dashed line shows the full sample estimate from column (1) in Table 2. The explanatory variables in the auxiliary forecasting equation for Δs_t are $\ln \text{HYS}_{t-2}$ and s_{t-2} (see the text for details).

in year $t+2$.[17] Second, in the next four panels, we sequentially replace real GDP growth per capita on the left-hand side of the regression with: (1) the growth of real business fixed investment; (2) the growth of real residential investment; (3) the growth in real durable goods consumption; and (4) the change in the unemployment rate. The time profile and statistical significance of the estimates are broadly similar to those for output growth. In most cases, we observe an effect that continues to accumulate over two years, before flattening out in year three.

What do the estimates in Table 4 imply in terms of economic magnitudes? Given that we are interested in understanding the effects of ex ante fluctuations in credit-market sentiment on real economic outcomes at a business cycle frequency, perhaps the most useful way to think about the magnitudes implied by the regression coefficients is in terms of a moderately sized move in the fitted value $\Delta\hat{s}_t$. Thus for example, we can ask what the implications are for cumulative output

[17]The reader may notice that the estimate of the coefficient on $\Delta\hat{s}_t$ at the forecast horizon $h = 0$ in Panel A of Table 4 differs slightly from that reported in column (1) of Panel A in Table 3. This small difference reflects the fact that in Table 4 we estimate the output growth regressions at all three forecast horizons jointly for consistency. As a result, the coefficient estimate on $\Delta\hat{s}_t$ at the forecast horizon $h = 0$ in Table 4 is based on a slightly different sample compared with that in Table 3 because we have lost two observations.

Table 3 – Subsample Analysis

Regressors	Dependent Variable: Δy_t (1)	(2)	(3)	(4)
A. *Sample Period:* 1952–2015				
$\Delta\hat{s}_t$	-2.680^{***}	.	-2.552^{***}	-3.169^{***}
	(0.576)		(0.628)	(0.945)
$\hat{r}_t^{SP}$	.	0.066^{*}	0.019	.
		(0.036)	(0.039)	
Δy_{t-1}	0.227	0.153	0.229	0.125
	(0.157)	(0.128)	(0.158)	(0.150)
$\Delta i_{t-1}^{(3m)}$	.	.	.	0.291^{*}
				(0.172)
$\Delta i_{t-1}^{(10y)}$	.	.	.	-0.153
				(0.225)
π_{t-1}	.	.	.	-0.272^{***}
				(0.087)
R^2	0.099	0.035	0.100	0.225
B. *Sample Period*: 1952–2007				
$\Delta\hat{s}_t$	-2.910^{***}	.	-3.041^{***}	-3.903^{***}
	(0.679)		(0.950)	(1.308)
$\hat{r}_t^{SP}$	.	0.029	-0.027	.
		(0.041)	(0.068)	
Δy_{t-1}	0.122	0.064	0.116	-0.028
	(0.128)	(0.127)	(0.142)	(0.117)
$\Delta i_{t-1}^{(3m)}$	.	.	.	0.330
				(0.194)
$\Delta i_{t-1}^{(10y)}$	.	.	.	-0.172
				(0.186)
π_{t-1}	.	.	.	-0.365^{***}
				(0.076)
R^2	0.101	0.001	0.102	0.324

Note: The dependent variable is Δy_t, the log-difference of real GDP per capita from year $t-1$ to year t. Regressors: $\Delta\hat{s}_t$ = predicted change in the Baa-Treasury spread; $\hat{r}_t^{SP}$ = predicted S&P 500 total (log) return; $\Delta i_t^{(3m)}$ = change in the 3-month Treasury yield; $\Delta i_t^{(10y)}$ = change in the 10-year Treasury yield; and π_t = CPI inflation. See the text and notes to Table 2 for details regarding the auxiliary forecasting equations for Δs_t, and r_t^{SP}. All specifications include a constant (not reported) and are estimated jointly with their auxiliary forecasting equation(s) by NLLS. Heteroskedasticity- and autocorrelation-consistent asymptotic standard errors reported in parentheses are computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994): * $p < .10$; ** $p < .05$; and *** $p < .01$.

growth over the period from t to $t+1$ when $\Delta\hat{s}_t$—which is our proxy for credit-market sentiment—moves from the 25th to the 75th percentile of its distribution, which corresponds to a 30-basis-point increase in $\Delta\hat{s}_t$. For real GDP per capita, the answer is that the cumulative growth impact from a sentiment move of this magnitude is around 1.2 percentage points. And, again, it bears emphasizing that in undertaking this thought experiment, we are asking how movements in output growth over

TABLE 4 – Different Horizons and Measures of Economic Activity

	Forecast Horizon (years)		
	$h = 0$	$h = 1$	$h = 2$
A. *Dep. Variable: real GDP per capita*			
$\Delta\hat{s}_t$	-2.726^{***}	-1.479^{**}	0.384
	(0.573)	(0.606)	(0.774)
Cumulative effect (pct.)[a]	-0.786^{***}	-1.213^{***}	-1.102^{**}
	(0.165)	(0.300)	(0.465)
B. *Dep. Variable: real business fixed investment*			
$\Delta\hat{s}_t$	-9.202^{***}	-7.548^{***}	-2.414
	(1.346)	(1.594)	(1.670)
Cumulative effect (pct.)	-2.653^{***}	-4.830^{***}	-5.527^{***}
	(0.388)	(0.700)	(0.981)
C. *Dep. Variable: real residential investment*			
$\Delta\hat{s}_t$	-16.794^{***}	-7.654^{*}	1.642
	(2.909)	(3.981)	(6.137)
Cumulative effect (pct.)	-4.843^{***}	-7.050^{***}	-6.576^{**}
	(0.839)	(1.549)	(2.766)
D. *Dep. Variable: real durable goods consumption*			
$\Delta\hat{s}_t$	-7.788^{***}	-2.355	4.328^{*}
	(1.943)	(1.739)	(2.614)
Cumulative effect (pct.)	-2.246^{***}	-2.925^{***}	-1.677
	(0.560)	(0.826)	(1.270)
E. *Dep. Variable: unemployment rate*			
$\Delta\hat{s}_t$	1.579^{***}	1.092^{***}	0.352
	(0.309)	(0.350)	(0.464)
Cumulative effect (pps.)	0.455^{***}	0.770^{***}	0.872^{***}
	(0.089)	(0.178)	(0.300)

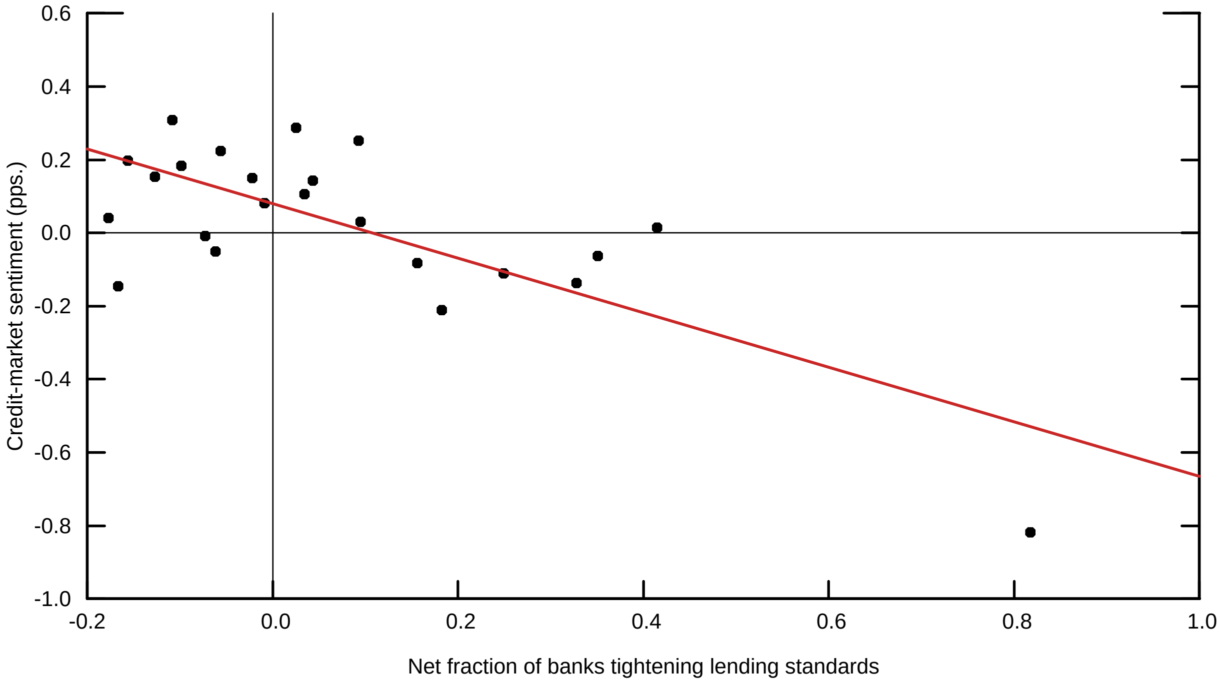
NOTE: Sample period: annual data from 1952 to 2015. In each panel, the dependent variable is Δy_{t+h}, the log-difference (simple difference in the case of the unemployment rate) in specified indicator of economic activity from year $t+h-1$ to year $t+h$. The entries denote the estimates of the coefficients associated with $\Delta\hat{s}_t$, the predicted change in the Baa-Treasury spread; additional explanatory variables (not reported) include Δy_{t-1}. The explanatory variables in the auxiliary forecasting equation for Δs_t are $\ln \text{HYS}_{t-2}$ and s_{t-2} (see the text and notes to Table 2 for details). All specifications include a constant (not reported) and are estimated jointly with the auxiliary forecasting equation for Δs_t by NLLS. Heteroskedasticity- and autocorrelation-consistent asymptotic standard errors reported in parentheses are computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994): * $p < .10$; ** $p < .05$; and *** $p < .01$.

[a] The entries denote the estimated cumulative effect of a deterioration in credit-market sentiment from P25 to P75 of its historical distribution—a 29-basis-point increase in $\Delta\hat{s}_t$—on the specified measure of economic activity between $t-1$ and $t+h$.

years t and $t+1$ respond to changes in the year $t-2$ value of sentiment. Seen in this light, our estimates would seem to imply economically interesting magnitudes.

For the other economic variables, we also obtain noteworthy effects. The same 25th-to-75th-percentile change in credit-market sentiment as of $t-2$ forecasts a cumulative decline in business

Figure 5 – Bank Lending Standards and Credit-Market Sentiment, 1991–2015



Note: The x-axis shows the average net fraction of banks that reported in the quarterly Senior Loan Officer Opinion Surveys in year t that they had tightening lending standards on loans to businesses and households (see Bassett, Chosak, Driscoll, and Zakrajšek, 2014). The y-axis shows the estimate of credit-market sentiment in year t from the auxiliary forecasting regression in column (1) of Panel A in Table 3.

fixed investment of 4.8 percentage points over the period t to $t+1$, declines of 7.1 percentage points and 2.9 percentage points in residential investment and durable goods consumption respectively, and a cumulative increase in the unemployment rate of about 0.8 percentage points.[18]

In thinking about these magnitudes, it is useful to bear in mind the following point. While our measure of credit-market sentiment is based on data from the corporate bond market, we do not mean to suggest that the only channel of economic transmission runs literally through just the supply of bond-market credit—which is probably too small to be responsible for such large effects across a range of economic indicators. Rather, we have in mind that the pricing of credit risk in the bond market is likely to be closely linked to the pricing of credit risk in the banking system. And while the former is easier for us to measure empirically, we suspect that the latter may be as or more important in terms of economic impact.

With this observation in mind, Figure 5 shows that there does appear to be a close link between the effective pricing of credit risk across the two markets. For the period from 1991 to 2015 for which we have data available, it plots our credit-sentiment measure against an indicator of changes

[18]As emphasized above, these numbers are arguably on the conservative side, in that we get substantially larger economic effects when we use the full 1929–2015 sample period to perform these calculations. For example, in Table B-4 of Appendix B, we show that the corresponding impacts on GDP and unemployment are 3.2 and 1.4 percentage points, respectively, in the longer sample.

Table 5 – Alternative Measures of Credit-Market Sentiment

	Dependent Variable: Δy_t					
	1929–2015	1952–2015	1973–2015			
Regressors	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\hat{s}_t$	-3.993^{***}	-2.981^{***}	-3.425^{***}	-3.050^{***}	-3.016^{***}	-2.754^{***}
	(0.929)	(1.081)	(0.620)	(0.943)	(0.928)	(0.925)
Δy_{t-1}	0.563^{***}	0.130	0.496^{***}	0.342^{*}	0.509^{***}	0.395^{**}
	(0.091)	(0.148)	(0.146)	(0.177)	(0.134)	(0.162)
R^2	0.378	0.174	0.312	0.409	0.226	0.365
	Auxiliary Regressions for Δs_t					
$\ln \text{HYS}_{t-2}$	0.112^{***}	0.137^{***}	0.111^{***}	0.144^{***}	.	.
	(0.030)	(0.050)	(0.020)	(0.048)		
s_{t-2}	-0.216^{***}	-0.091^{*}	-0.268^{***}	-0.173^{***}	.	.
	(0.045)	(0.049)	(0.080)	(0.039)		
TS_{t-2}	-0.108^{***}	-0.146^{***}	.	-0.141^{***}	.	-0.164^{***}
	(0.036)	(0.031)		(0.029)		(0.054)
EBP_{t-2}	.	.	.	.	-0.443^{***}	-0.432^{***}
					(0.124)	(0.121)
R^2	0.135	0.108	0.088	0.138	0.077	0.149

Note: The dependent variable is Δy_t, the log-difference of real GDP per capita from year $t-1$ to year t. Regressors: $\Delta\hat{s}_t$ = predicted change in the Baa-Treasury spread. In the auxiliary forecasting equations: HYS_t = fraction of debt that is rated as high yield (Greenwood and Hanson, 2013, the coefficient is multiplied by 100); TS_t = term spread; and EBP_t = excess bond premium (Gilchrist and Zakrajšek, 2012). All specifications include a constant (not reported) and are estimated jointly with their auxiliary forecasting equation for Δs_t by NLLS. Heteroskedasticity- and autocorrelation-consistent asymptotic standard errors reported in parentheses are computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994): * $p < .10$; ** $p < .05$; and *** $p < .01$.

in bank lending standards constructed by Bassett, Chosak, Driscoll, and Zakrajšek (2014), using bank-level responses to the Federal Reserve's Senior Loan Officer Opinion Survey. Perhaps not surprisingly, there is a close correlation between these two credit-supply indicators: In years in which our bond-market-based measure shows credit sentiment to be relatively upbeat, bank loan officers tend to report that they are easing credit standards on loans to businesses and households.

3.6 Additional Indicators of Credit-Market Sentiment

Thus far, we have used the lagged values of the credit spread and the high-yield share as our only predictors of changes in credit spreads. We have done so in part to discipline ourselves against the temptation to mine the data for other variables that forecast changes in credit spreads. In Table 5, we relax this discipline a bit. We begin by adding an additional variable—also identified by GH—to our forecasting regression for Δs_t, namely the level of the term spread at the end of year $t-2$, defined as the difference between the yields on 10-year and 3-month Treasury securities. Column (1) of the table shows that over the full sample period from 1929 to 2015, the term spread has substantial predictive power for future changes in corporate credit spreads. It attracts a significantly negative coefficient, while the coefficients on the other two measures of credit-market sentiment remain roughly unchanged; moreover, the R^2 of the first-step forecasting regression increases notably, from 0.10 to almost 0.14.

With this expanded set of variables, the estimate of the effect of $\Delta\hat{s}_t$ on Δy_t declines somewhat in absolute magnitude, from -4.80 to -3.99. However, given that we are ultimately interested in the effect of changes in ex ante credit-market sentiment, it is important to recognize that with the added variable in the first-step regression, we now trace out more variation in sentiment—that is, the fitted value $\Delta\hat{s}_t$ now has more variance. Therefore, when we revisit the economic significance calculations of the sort shown in Table 4, we actually get either similar or somewhat larger cumulative impacts. We will return to this point momentarily.

Column (2) of Table 5 redoes the analysis over our baseline (1952–2015) sample period, with similar results: Once again, the term spread is strongly significant in the first-step regression, and the coefficient on $\Delta\hat{s}_t$ in the second-step regression is now very close to that reported in Panel A of Table 3. Finally, columns (3) through (6) examine the period from 1973 to 2015; we do so because this even more recent period is the one over which we can compute the excess bond premium of Gilchrist and Zakrajšek (2012), which has a natural interpretation as an alternative measure of credit-market sentiment. As can be seen, the EBP behaves remarkably similarly to the combination of credit spreads and the high-yield share. It has significant predictive power in the first-step regression—either when entered on its own or in conjunction with the term spread—and it produces second-step estimates of the coefficient on $\Delta\hat{s}_t$ that are nearly the same as those based on the GH proxies. Thus our key results appear to be robust to the choice of forecasting variables used to identify credit-market sentiment.

As noted above, the notable increase in the explanatory power of the first-step regression resulting from the addition of the term spread to the baseline GH predictors implies greater variability in the fitted value $\Delta\hat{s}_t$, and hence larger economic effects, all else equal. We make this point explicit in Table B-5 of Appendix B, which covers the sample period from 1952 to 2015 and is identical in structure to Table 4, but relies on first-step estimates that use the expanded set of predictors, including the term spread. With this alternative specification, a move in $\Delta\hat{s}_t$ from the 25th to the 75th percentile of its historical distribution is now 45 basis points instead of 30 basis points. This implies a decline in real GDP growth of 1.7 percentage points over years t to $t+1$, as compared with the decline of 1.2 percentage points reported in Table 4; similarly, the cumulative impact on the unemployment rate increases from 0.8 percentage points to 1.1 percentage points. Thus, if anything, the baseline results reported in Table 4 appear to paint a somewhat conservative picture of the economic damage associated with an unwinding of credit-market sentiment.

3.7 Asymmetries: Overheating vs. Overcooling

Thus far, all of our specifications have imposed the restriction that changes in credit spreads and credit-market sentiment are associated with symmetric linear effects on real activity. In other words, to the extent that indicators of market overheating—unusually low credit spreads and high levels

Table 6 – Asymmetric Effects of Changes in Credit Spreads

	Dependent Variable: Δy_t			
	1929–2015	1952–2015	1973–2015	
Regressors	(1)	(2)	(3)	(4)
$\Delta s^{(+)}_{t-1}$	-2.304^{**}	-1.648^{***}	-1.459^{***}	.
	(0.957)	(0.325)	(0.273)	
$\Delta s^{(-)}_{t-1}$	-1.586^{***}	-0.838	-0.828^{*}	.
	(0.587)	(0.646)	(0.455)	
$\Delta \text{EBP}^{(+)}_{t-1}$	.	.	.	-2.331^{***}
				(0.566)
$\Delta \text{EBP}^{(-)}_{t-1}$	.	.	.	-0.542^{**}
				(0.252)
R^2	0.420	0.285	0.376	0.467
Difference[a]	-0.718	-0.810	-0.631	-1.789^{***}
	(0.769)	(0.720)	(0.495)	(0.648)

Note: The dependent variable is Δy_t, the log-difference of real GDP per capita from year $t-1$ to year t. The entries denote the OLS estimates of the coefficients associated with $\Delta s^{(+)}_{t-1}$ and $\Delta s^{(-)}_{t-1}$, the positive and negative changes in the Baa-Treasury spread, respectively, and $\Delta \text{EBP}^{(+)}_{t-1}$ and $\Delta \text{EBP}^{(-)}_{t-1}$, the positive and negative changes in the excess bond premium (Gilchrist and Zakrajšek, 2012), respectively. Additional explanatory variables (not reported) include a constant and Δy_{t-1}. Heteroskedasticity- and autocorrelation-consistent asymptotic standard errors reported in parentheses are computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994): * $p < .10$; ** $p < .05$; and *** $p < .01$.
[a] Difference between the estimated coefficients on $\Delta s^{(+)}_{t-1}$ and $\Delta s^{(-)}_{t-1}$ or $\Delta \text{EBP}^{(+)}_{t-1}$ and $\Delta \text{EBP}^{(-)}_{t-1}$.

of junk-bond issuance—are taken to be pessimistic signs for future real activity, our specifications also imply that indicators of overcooling should be thought of as containing optimistic news, all else equal.

As a matter of theory, this sort of symmetry does not seem implausible, at least as a first-order approximation. Our basic premise is that we can use our sentiment indicators to forecast changes in the supply of credit. In an overheated market, this maps into a prediction that credit supply will contract two years down the road, and in an overcooled market, the prediction is that supply will eventually expand. As long as we are away from a frictionless first-best situation where firms view externally obtained credit and internally generated sources of finance as perfect substitutes, a marginal change in credit supply in either direction might be expected to have similar effects on real activity.

Nevertheless, it is of obvious interest to see whether the data are suggestive of any asymmetries. Table 6 takes a first cut at the question. In column (1), we revisit our simple OLS regression from column (1) of Table 1, where changes in credit spreads in year $t-1$ are used to forecast changes in real GDP per capita in year t over the full (1929–2015) sample period; the one modification is that we now allow for different coefficients on credit-spread increases ($\Delta s^{(+)}_{t-1}$) and decreases ($\Delta s^{(-)}_{t-1}$). As can be seen, at -2.3, the estimate of the coefficient on credit-spread increases is moderately larger in absolute terms than the estimate of -1.6 of the coefficient on credit-spread decreases. This

TABLE 7 – Asymmetric Effects of Credit-Market Sentiment

	Dependent Variable: Δy_t		
Regressors	1929–2015	1952–2015	1973–2015
$\Delta\hat{s}_t^{(+)}$	-1.049	-2.609	-3.420^{**}
	(2.806)	(2.118)	(10.891)
$\Delta\hat{s}_t^{(-)}$	-5.955^{**}	-3.075^{*}	-2.713^{*}
	(2.741)	(2.259)	(2.293)
R^2	0.329	0.264	0.547
Difference[a]	4.907	0.466	-0.707
	(4.637)	(3.486)	(11.150)

NOTE: The dependent variable is Δy_t, the log-difference of real GDP per capita from year $t-1$ to year t. The entries denote the second-step OLS estimates of the coefficients associated with $\Delta\hat{s}_t^{(+)}$ and $\Delta\hat{s}_t^{(-)}$, the positive and negative predicted change in the Baa-Treasury spread, respectively; additional explanatory variables (not reported) include a constant and Δy_{t-1}. The explanatory variables in the auxiliary forecasting equation for Δs_t are $\ln \mathrm{HYS}_{t-2}$, s_{t-2}, and TS_{t-2} (see the text and notes to Table 5 for details). To take into account the generated regressors $\Delta\hat{s}_t^{(+)}$ and $\Delta\hat{s}_t^{(-)}$ in the second-step regressions, the standard errors reported in parentheses are based on the stationary block bootstrap procedure (20,000 replications) of Politis and Romano (1994): * $p < .10$; ** $p < .05$; and *** $p < .01$.

[a] The difference between the estimated coefficients on $\Delta\hat{s}_t^{(+)}$ and $\Delta\hat{s}_t^{(-)}$.

loosely suggests that contractions in the supply of credit are associated with stronger effects on future economic growth than increases in credit availability. However, the difference between these two effects is not statistically significant. Columns (2) and (3) display qualitatively similar results for the sample periods 1952–2015 and 1973–2015, respectively: The coefficients associated with credit-spread increases are again larger in absolute terms than those for credit-spread decreases, but not statistically so. Finally, column (4) looks at asymmetric changes in the EBP instead of in raw credit spreads, thereby attempting to capture a purer measure of a change in sentiment. In this one case, the effect of a tightening in credit conditions appears to be statistically distinguishable from the effect of an easing.[19]

In Table 7, we perform a similar analysis, but now looking for asymmetries not in the impact of realized changes in credit spreads, but rather in the impact of our fitted two-step measure of credit-market sentiment $\Delta\hat{s}_t$. That is, we allow positive and negative values of $\Delta\hat{s}_t$—denoted by $\Delta\hat{s}_t^{(+)}$ and $\Delta\hat{s}_t^{(-)}$, respectively—to enter the second-step regression with different coefficients. Column (1) of the table shows the results for the full (1929–2015) sample period. Here the point estimates yield a striking asymmetry: The effect of negative values of $\Delta\hat{s}_t$ is much larger in absolute magnitude than the effect of positive values. This would seem to suggest that our earlier results are largely driven by market *overcooling*—times when credit-market sentiment is unusually depressed and spreads are expected to narrow going forward. However, given the handful of highly influential outliers in the early part of this sample, the large difference in point estimates is not statistically significant.

Columns (2) and (3) replicate the specification of column (1) for the shorter and better-behaved

[19]This asymmetry with respect to the predictive power of the EBP measure was previously noted by Stein (2014).

sample periods of 1952 to 2015 and 1973 to 2015, respectively. Now the coefficients on positive and negative values of $\Delta\hat{s}_t$ are much closer in magnitude, suggesting that waves of overheating and overcooling in credit markets play a roughly equal role in shaping our results for these more recent periods.

Overall then, we find little statistically robust evidence of asymmetries in the data. Some of this non-result—particularly with our two-step approach applied to the 1929–2015 sample period—may say more about outliers and the associated lack of statistical power than anything else. However, even in more recent sample periods when the data are less noisy, there does not seem to be decisive evidence of an asymmetry in one direction or the other.

3.8 Comparison with Balance-Sheet Measures of Leverage

As discussed in Section 2, our interest in behavioral theories of the credit cycle has led us to focus on expected-return-based measures of credit-market sentiment. This approach stands in contrast to much of the recent empirical literature on credit cycles, which has utilized balance-sheet measures of leverage. We now attempt to reconcile our results with those in the balance-sheet vein.

In their influential work, Schularick and Taylor (2012) and Jordà, Schularick, and Taylor (2013) use a long panel data set covering 14 countries over the period 1870 to 2008 to document that lagged bank credit growth forecasts future output growth with a negative sign. They interpret this pattern as evidence that "credit booms gone bust" can have adverse macroeconomic consequences. This hypothesis is broadly similar in spirit to ours, though again it puts more emphasis on balance-sheet fragility—in this case, the balance sheet of the banking system—as opposed to the mispricing of credit assets. In any event, it is of interest to see if there is independent information in their key predictive variables and ours.

In columns (1) and (2) of the top panel of Table 8, we run regressions over the full (1929–2015) sample period that resemble those of Schularick and Taylor (2012) and Jordà, Schularick, and Taylor (2013), albeit in our much-restricted one-country sample. In column (1), we run an OLS regression of Δy_t—the log-difference in real GDP per capita from year $t-1$ to year t—on its once-lagged value and on the log-difference in real bank credit over the 5-year period ending in year $t-2$ ($\Delta_5 \ln \mathrm{BC}_{t-2}$). Here, bank credit is defined as the sum of bank loans plus securities holdings. In column (2), we do the same thing, but use instead the 5-year log-difference in real bank loans ($\Delta_5 \ln \mathrm{BL}_{t-2}$), rather than total bank credit.[20] In both cases, we obtain the expected negative coefficients, confirming that there does indeed appear to be a dark side to bank credit booms; however, only the coefficient in column (1) is statistically significant.

In columns (3) and (4), we run horse races that include these bank credit growth variables alongside the predicted change in the credit spread $\Delta\hat{s}_t$. As can be seen, credit-market sentiment holds up well in competition with the growth in bank balance sheet variables. When pitted against

[20] We use measures of bank balance sheet growth that end in year $t-2$ so as to maintain comparability with the fitted change in the credit spread $\Delta\hat{s}_t$, which is also based on data available at $t-2$. However, our results are qualitatively and quantitatively very similar if we vary the timing, so that bank balance sheet growth is instead computed over the period ending at $t-1$.

TABLE 8 – Bank Balance Sheets

Regressors	Dependent Variable: Δy_t (1)	(2)	(3)	(4)
A. *Sample Period:* 1929–2015				
$\Delta\hat{s}_t$	.	.	-4.480^{***}	-4.333^{***}
			(0.779)	(1.400)
$\Delta_5 \ln \mathrm{BC}_{t-2}$	-0.294^{***}	.	-0.354^{**}	.
	(0.089)		(0.137)	
$\Delta_5 \ln \mathrm{BL}_{t-2}$	.	-0.052	.	0.053
		(0.067)		(0.079)
R^2	0.329	0.291	0.404	0.384
B. *Sample Period:* 1952–2015				
$\Delta\hat{s}_t$	.	.	-2.964^{***}	-2.993^{**}
			(1.135)	(1.161)
$\Delta_5 \ln \mathrm{BC}_{t-2}$	-0.071	.	-0.018	.
	(0.140)		(0.169)	
$\Delta_5 \ln \mathrm{BL}_{t-2}$	.	-0.042	.	0.008
		(0.068)		(0.094)
R^2	0.022	0.021	0.174	0.174

NOTE: The dependent variable is Δy_t, the log-difference of real GDP per capita from year $t-1$ to year t. Regressors: $\Delta\hat{s}_t$ = predicted change in the Baa-Treasury spread and 5-year (annualized) growth in various measures of commercial bank balance sheets: BC_t = (inflation-adjusted) bank credit (loans + securities); and BL_t = (inflation-adjusted) bank loans. All specifications include Δy_{t-1} (not reported). The explanatory variables in the auxiliary forecasting equation for Δs_t (columns 3–4) are $\ln \mathrm{HYS}_{t-2}$, s_{t-2}, and TS_{t-2}, where HYS_t denotes the fraction of debt that is rated as high yield (Greenwood and Hanson, 2013) and TS_t is the term spread. All specifications include a constant (not reported); those in columns 1–2 are estimated by OLS, while those in columns 3–4 are estimated jointly with the auxiliary forecasting equation for Δs_t by NLLS. Heteroskedasticity- and autocorrelation-consistent asymptotic standard errors reported in parentheses are computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994): * $p < .10$; ** $p < .05$; and *** $p < .01$.

bank loan growth in column (4), the coefficient on $\Delta\hat{s}_t$ is actually a bit larger in absolute terms than its baseline value of -3.99 from column (1) of Table 5, while the coefficient on real bank loan growth is statistically insignificant and even of the wrong sign. In column (3), real bank credit growth fares better, retaining its statistical significance, but the coefficient on $\Delta\hat{s}_t$ remains strongly significant and virtually unchanged in magnitude.

The lower panel of Table 8 is identical to the upper panel, except that it focuses on the shorter 1952–2015 sample period. Here the distinction between the growth of bank balance sheets and credit-market sentiment is starker: Neither of the bank-balance-sheet variables is significant in any of the specifications, while the coefficient on $\Delta\hat{s}_t$ remains very close to its value from column (2) of Table 5.

While these results are striking, we caution against over-interpreting them. The relatively weaker performance of the bank credit variables in our U.S.-only sample in no way contradicts the results of Schularick and Taylor (2012) and Jordà, Schularick, and Taylor (2013), which are based

TABLE 9 – Other Balance-Sheet Measures of Leverage

	Dependent Variable: Δy_t			
Regressors	(1)	(2)	(3)	(4)
$\Delta \hat{s}_t$	-2.956^{***}	-2.983^{***}	-2.912^{**}	-2.979^{***}
	(1.109)	(1.046)	(1.141)	(1.087)
$\Delta_5 \ln[\text{PNF/GDP}]_{t-2}$	-0.074	.	.	.
	(0.137)			
$\Delta_5 \ln[\text{NFB/GDP}]_{t-2}$	.	-0.003	.	.
		(0.127)		
$\Delta_5 \ln[\text{HH/GDP}]_{t-2}$	.	.	-0.077	.
			(0.089)	
$\Delta_5 \ln[D/A]_{t-2}$	.	.	.	0.046
				(0.085)
R^2	0.178	0.174	0.183	0.175

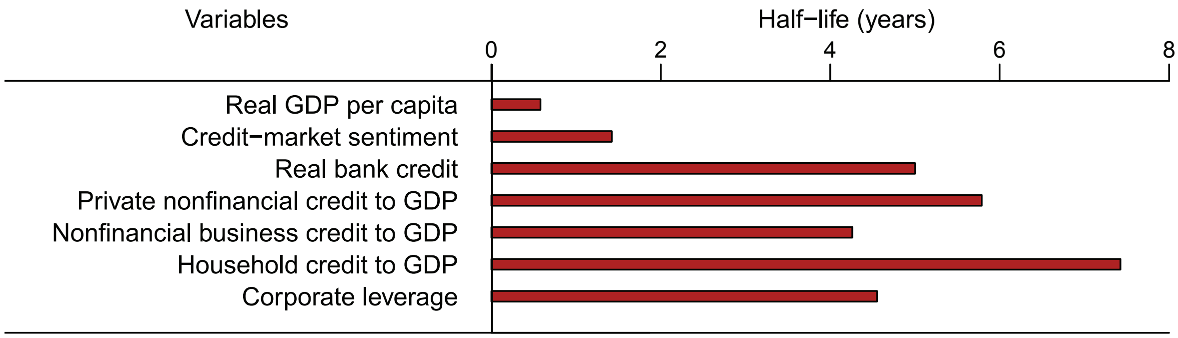
NOTE: Sample period: annual data from 1952 to 2015. The dependent variable is Δy_t, the log-difference of real GDP per capita from year $t-1$ to year t. Regressors: $\Delta \hat{s}_t$ = predicted change in the Baa-Treasury spread; 5-year (annualized) growth in various ratios of sectoral credit outstanding to nominal GDP (columns 1–3) and 5-year (annualized) growth in corporate leverage (column 4): PNF_t = private nonfinancial sector credit; NFB_t = nonfinancial business sector credit; HH_t = household sector credit; and $[D/A]_t$ = debt to assets ratio for nonfinancial corporate sector. All specifications include Δy_{t-1} (not reported). The explanatory variables in the auxiliary forecasting equation for Δs_t are $\ln \text{HYS}_{t-2}$, s_{t-2}, and TS_{t-2}, where HYS_t denotes the fraction of debt that is rated as high yield (Greenwood and Hanson, 2013) and TS_t is the term spread. All specifications include a constant (not reported) and are estimated jointly with the auxiliary forecasting equation for Δs_t by NLLS. Heteroskedasticity- and autocorrelation-consistent asymptotic standard errors reported in parentheses are computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994): * $p < .10$; ** $p < .05$; and *** $p < .01$.

on a much larger 14-country sample. Indeed, as we argue in more detail below, this cross-country panel approach turns out to be critical for regressions that use any of the balance-sheet measures of financial fragility. This is because the balance-sheet measures tend to be highly persistent—much more so than our sentiment-based proxies—and so there is simply not enough power in a relatively short single-country sample to reliably discern their effects.

Table 9 extends the analysis to consider four other balance-sheet measures of financial fragility. These include the five-year growth rates of: (1) private nonfinancial credit to GDP; (2) nonfinancial business sector credit to GDP; (3) household sector credit to GDP (as in Mian, Sufi, and Verner (2016)); and (4) corporate leverage, defined as the ratio of debt to assets for the nonfinancial corporate sector. In each case, we enter the twice-lagged value of the given balance-sheet measure in the regression alongside $\Delta \hat{s}_t$ and focus on the sample period from 1952 to 2015, so the specifications exactly mirror those for the bank-balance-sheet variables in columns (3) and (4) of Panel B in Table 8. Interestingly, we get very similar results: In all four cases, the balance-sheet measures are completely insignificant in terms of predicting future output growth, while the coefficients on $\Delta \hat{s}_t$ remain almost exactly as they were in the previous table.[21]

[21]For corporate leverage, we have also used firm-level Compustat data to create time series that focus more specifically on the leverage of the most vulnerable firms in the economy, which might arguably be more relevant for

Figure 6 – Persistence of Selected Macroeconomic Variables, 1952–2015



Note: The horizontal bars depict the estimated half life of the specified macroeconomic variable, based on the impulse response function from a univariate AR model: real GDP per capita (log-difference, AR(2)); credit-market sentiment (the predicted value of Δs_t, using $\ln \mathrm{HYS}_{t-2}$, s_{t-2}, and TS_{t-2} as predictors, AR(3)); real bank credit (5-year (annualized) log-difference, AR(4)) various ratios of sectoral credit outstanding to nominal GDP (5-year (annualized) log-difference, AR(4)); and debt to assets ratio for nonfinancial corporate sector (5-year (annualized) log-difference, AR(4)). See the text and notes to Tables 8 and 9 for details.

Why does our measure of credit-market sentiment perform so much better than any of the balance-sheet measures in our U.S.-only sample? Figure 6 offers one possible clue. The figure shows estimates of the half-life of seven variables: real GDP per capita growth; our credit-sentiment variable; and five of the balance-sheet measures. As can be seen, all of the balance-sheet proxies are highly persistent, with half-lives of between four and eight years; of these, the Mian, Sufi, and Verner (2016) household-debt variable has, at almost 7.5 years, the longest half-life. By contrast, the credit-sentiment measure is much less persistent, with a half-life of only about 1.4 years. So if we restrict ourselves to a roughly 60-year sample period from a single country, the balance-sheet measures are inevitably going to face challenges because there are simply too few independent observations to generate enough statistical power. It is thus no accident that the research using these balance-sheet measures has relied on multi-country panels—given the persistence of the series, this is the only viable approach. However, because credit sentiment is more strongly mean-reverting, we can reliably estimate its effects on real activity in a single-country time series.

It is instructive to tie this all back to our earlier discussion of vulnerabilities and triggers. Recall that as a matter of theory, models in the financial-frictions genre give little guidance as to the timing of a downturn because they are models of amplification and propagation that for the most part do not take a stand on the shock that sets the system in motion. Thus if such exogenous shocks are infrequent and balance-sheet measures of leverage by their nature evolve gradually, one

measuring overall fragility. For example, we computed for each year the debt-to-assets ratio for firms at the 75th and 90th percentiles of the (sales-weighted) cross-sectional distribution of nonfinancial firms. Using these alternative metrics yields similar results to those reported above. So too does pushing back the aggregate corporate leverage series to 1929, drawing on work by John Graham, Mark Leary, and Michael Roberts (2015), who generously shared their historical data on corporate balance sheets with us. In all cases, the general conclusion is the same: Measures of corporate leverage have little explanatory power for future GDP growth, while the coefficients on $\Delta \hat{s}_t$ are unaffected by including any of these variables.

would not expect to see much high-frequency action in the data, and the impression created might be of a credit cycle that has a long duration. However, a more precise interpretation would be that absent a triggering event, the economy can remain in a relatively vulnerable high-leverage state for a number of years.

Conversely, sentiment-based models, which emphasize the endogenous unwinding of over-optimistic beliefs, can be thought of as helping to calibrate the time-varying probability of a trigger event. That is, depending on the dynamics of belief revisions, once asset prices are significantly elevated, such models may be able to tell us that a reversal is in expectation relatively close at hand. And indeed, the considerably shorter half-life of the credit-sentiment variable suggests that these higher-frequency dynamics are present in the data.

Of course, as we have stressed above, it may be somewhat unnatural to pit the sentiment-based and balance-sheet-based measures against each other as competitors in an empirical horse race. Rather, the vulnerabilities-plus-triggers framing suggests an interactive specification. That is, the predictive power of elevated credit-market sentiment should be stronger in the presence of high debt levels, when the economy is in a more fragile state.

Table 10 presents a series of interactive regressions of this sort. In column (1), we regress real GDP per capita growth in year t on: its own lag; our credit-sentiment proxy $\Delta\hat{s}_t$; the annualized five-year growth rate of non-financial business credit to GDP, measured as of year $t-2$; and the interaction of the latter two variables. In column (2), we keep everything else the same but use the annualized five-year growth of household credit to GDP instead of the growth of business credit. Columns (3) and (4) then replicate columns (1) and (2), but instead of using five-year growth rates of the balance-sheet variables, they use "gaps," where these gaps are defined as the deviation of the log-level of the variable from its trend, which is in turn estimated using the linear projection method of Hamilton (2016).

The results paint a fairly consistent picture.[22] Across all four specifications, the key interaction coefficient is negative, as expected, meaning that the impact of $\Delta\hat{s}_t$ on GDP growth is stronger in absolute magnitude when leverage is high. Moreover, the implied quantitative effects are quite substantial. We illustrate this in the table by comparing the impact of $\Delta\hat{s}_t$ on GDP growth when the balance-sheet variable in question is at the 90th percentile of its distribution, as opposed to the 10th percentile; depending on the specification, the former is between 1.5 and 3.3 times the latter. However, in only one of the four regressions is the interaction coefficient statistically significant. This too, might have been expected, given the power limitations associated with the balance-sheet measures in our U.S.-only sample.

In sum, the interactive specifications in Table 10 are broadly consistent with a triggers-plus-vulnerabilities account of credit cycles—one that features a complementary role for both behavioral factors and financial frictions. However, given the persistence of the balance-sheet variables and the associated lack of statistical significance, the evidence from our sample can at best be only

[22]We have experimented at some length with the other balance-sheet measures of leverage and with different methods of detrending, with generally similar results.

Table 10 – Interactive Specifications: Credit-Market Sentiment and Leverage

	Dependent Variable: Δy_t			
Regressors	(1)	(2)	(3)	(4)
$\Delta\hat{s}_t$	-3.043^{***}	-3.000^{**}	-3.597^{**}	-3.452^{***}
	(1.095)	(1.234)	(1.537)	(1.293)
$\Delta_5 \ln[\text{NFB/GDP}]_{t-2}$	0.006	.	.	.
	(0.115)			
$\Delta\hat{s}_t \times \Delta_5 \ln[\text{NFB/GDP}]_{t-2}$	-29.709	.	.	.
	(41.660)			
$\Delta_5 \ln[\text{HH/GDP}]_{t-2}$	.	-0.071	.	.
		(0.091)		
$\Delta\hat{s}_t \times \Delta_5 \ln[\text{HH/GDP}]_{t-2}$	.	-39.532	.	.
		(34.972)		
$\text{gap}[\text{NFB/GDP}]_{t-2}$	.	.	-0.020	.
			(0.067)	
$\Delta\hat{s}_t \times \text{gap}[\text{NFB/GDP}]_{t-2}$	.	.	-43.016^{***}	.
			(11.358)	
$\text{gap}[\text{HH/GDP}]_{t-2}$	.	.	.	-0.025
				(0.052)
$\Delta\hat{s}_t \times \text{gap}[\text{HH/GDP}]_{t-2}$	.	.	.	-34.379
				(24.617)
R^2	0.178	0.191	0.221	0.202
Effect of $\Delta\hat{s}_t$ on Δy_t (pct.)[a]				
At P10 of a credit aggregate	-1.073	-0.814	-0.791	-0.884
	(0.656)	(0.874)	(0.698)	(0.653)
At P90 of a credit aggregate	-1.609^{***}	-1.906^{***}	-2.624^{***}	-2.392^{***}
	(0.587)	(0.558)	(0.772)	(0.973)

Note: Sample period: annual data from 1952 to 2015. The dependent variable is Δy_t, the log-difference of real GDP per capita from year $t-1$ to year t. Regressors: $\Delta\hat{s}_t$ = predicted change in the Baa-Treasury spread; demeaned 5-year (annualized) growth in ratios of sectoral credit outstanding to nominal GDP (columns 1–2) and corresponding sectoral credit-to-GDP gaps (columns 3–4), where a gap is defined as a deviation of a (log) ratio of a sector-specific credit aggregate to nominal GDP from its respective trend, estimated using the linear projection method of Hamilton (2016); and interactions of $\Delta\hat{s}_t$ with sectoral credit aggregates: NFB_t = nonfinancial business sector credit; and HH_t = household sector credit. All specifications include Δy_{t-1} (not reported). The explanatory variables in the auxiliary forecasting equation for Δs_t are $\ln \text{HYS}_{t-2}$, s_{t-2}, and TS_{t-2}, where HYS_t denotes the fraction of debt that is rated as high yield (Greenwood and Hanson, 2013) and TS_t is the term spread. All specifications include a constant (not reported) and are estimated jointly with the auxiliary forecasting equation for Δs_t by NLLS. Heteroskedasticity- and autocorrelation-consistent asymptotic standard errors reported in parentheses are computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994): * $p < .10$; ** $p < .05$; and *** $p < .01$.

[a] The estimated effect of a deterioration in credit-market sentiment from P25 to P75 of its historical distribution—a 45-basis-point increase in $\Delta\hat{s}_t$—on the growth of real GDP per capita between $t-1$ and t, evaluated at the specified percentile of the historical distribution of a sector-specific credit aggregate.

suggestive. Further progress will require cross-country data that incorporates measures of both credit-market sentiment and balance-sheet fragility. Krishnamurthy and Muir (2016), who find evidence of interaction effects in their broader cross-country sample, is an example of just this sort of work.

4 Exploring the Mechanism

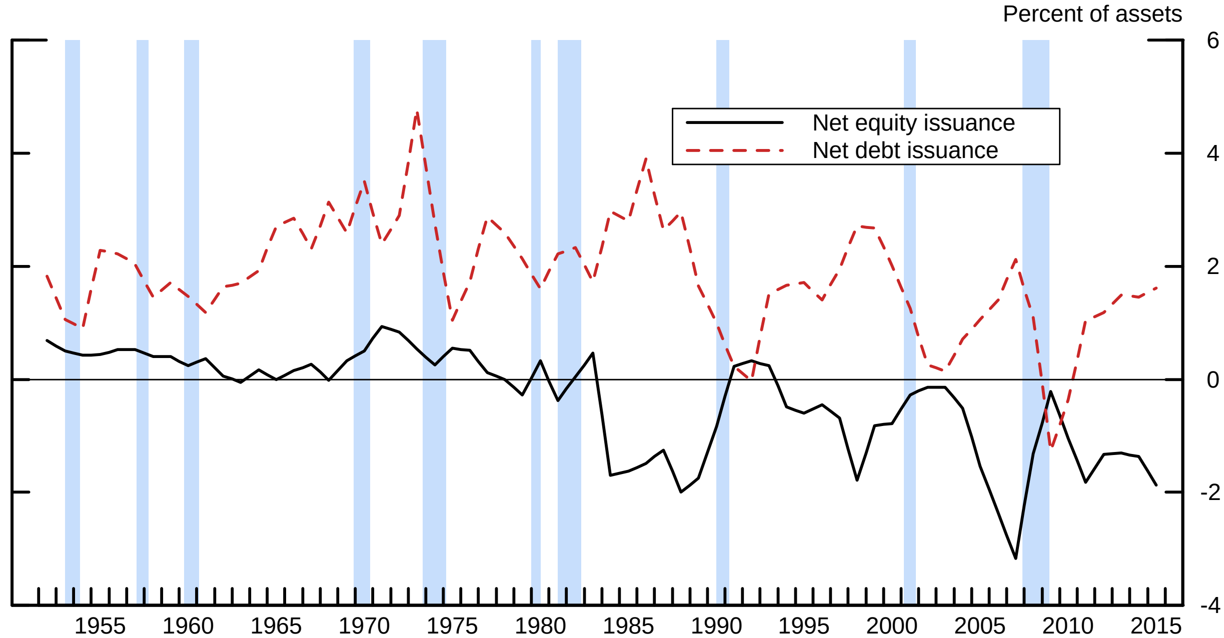
In the previous section, we showed that heightened levels of credit-market sentiment are bad news for future economic activity. Our working hypothesis is that when sentiment is running high, it is more likely to reverse itself over the next couple of years, and the associated widening of credit spreads amounts to a reduction in the supply of credit, which in turn impinges on the real economy. However, there is an alternative interpretation of our results that does not involve reversals of credit supply. As argued by Rognlie, Shleifer, and Simsek (2016), it may be that during credit booms, generalized optimism leads to over-investment in some sectors, and it is this inefficient investment that makes the economy vulnerable to a future downturn—even absent a subsequent inward shift in credit supply. In other words, our sentiment proxies may be predicting something not about future credit supply, but rather about future credit demand.

In this section, we attempt to disentangle these hypotheses. We do so by conducting two types of tests. First, we ask whether our proxy for credit-market sentiment predicts not only changes in real activity, but also changes in the aggregate debt-equity mix for nonfinancial firms. The intuition here—which we sketch in Appendix C with a simple model—is straightforward. Suppose we know that credit-market sentiment at time $t-2$ forecasts a decline in investment at time t. This could be either: (1) because the sentiment proxy forecasts a reduction in the appeal of future investment, as would be implied by Rognlie, Shleifer, and Simsek (2016); or (2) because the sentiment proxy forecasts an increase in the future cost of credit. Based on observation of just investment (or real activity more generally), these two alternatives cannot be separated. However, looking at the firm's financing mix can help because there is no obvious reason for the financing mix to be influenced by investment demand. Thus if both investment and the debt-to-equity ratio fall, this can more readily be explained by an increase in the cost of debt relative to the cost of equity—that is, by an inward shift in the supply of credit in a world in which the credit and equity markets are partially segmented. This observation motivates our first set of tests, which focus on relative movements in aggregate net debt and net equity issuance of U.S. nonfinancial firms.

Second, we undertake a set of cross-sectional tests. These follow from noting that if our credit-sentiment proxy is able to forecast market-wide changes in the effective cost of credit, these changes should be more pronounced for lower credit-quality firms. This is because such firms have, in effect, a higher loading on the aggregate market factor. In other words, the ratio of price-to-fundamentals falls by more for a Caa-rated issuer than for an Aa-rated issuer when market-wide sentiment deteriorates. This implies that when credit-market sentiment is elevated at time $t-2$, we should expect that at time t firms with lower credit ratings will exhibit a larger drop in their investment.

Before proceeding, however, we note a caveat on the interpretation: These tests can at best provide evidence that is *qualitatively* consistent with our credit-supply hypothesis. They cannot be used to make the *quantitative* case that credit-supply effects are predominantly responsible for the

Figure 7 – Corporate Financing Mix



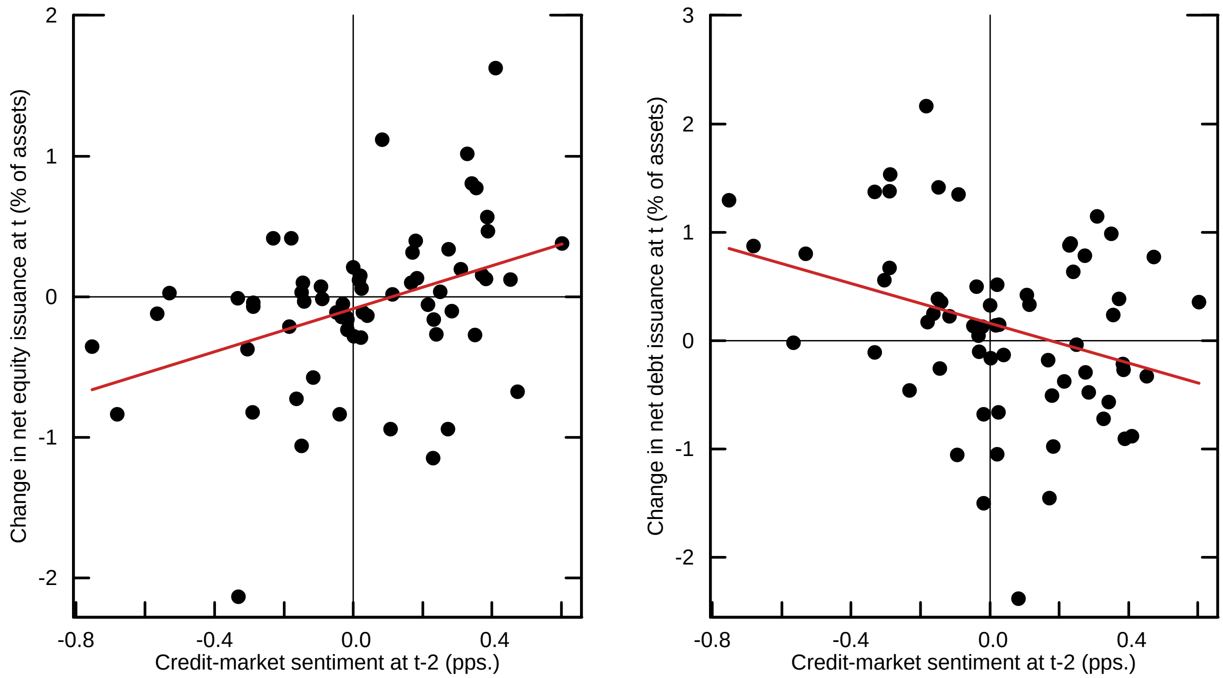
Note: The solid line depicts net equity issuance in the U.S. nonfinancial corporate sector, while the dotted line depicts net (long-term) debt issuance; both series are expressed as a percent of the beginning-of-period book-value of total assets. The shaded vertical bars denote the NBER-dated recessions.

size of the macroeconomic effects documented in Section 3. As one example, while we find that our credit-sentiment proxy forecasts a significant decline in the capital expenditures of junk-rated firms relative to those of investment-grade firms, we would not want to argue that the investment behavior of the junk-rated firms explains most of the aggregate business cycle effects. Even if a credit-supply channel is at work, it is presumably operating across a variety of other sectors as well—including households and firms that borrow not just from the bond market, but from banks as well. Our focus on junk-rated versus investment-grade firms makes for a simple test with a well-defined control group, but it obviously misses these other channels of transmission.

4.1 Evidence from the Corporate Financing Mix

Our first set of tests uses data from the Financial Accounts of the United States from 1952 to 2015 on the aggregate net debt and net equity issuance of the U.S. nonfinancial corporate sector. These two series (expressed as a percent of beginning-of-period assets) are plotted in Figure 7. As pointed out by Ma (2016), there is a striking negative correlation between the two series beginning in the early 1980s—meaning that when net debt issues go up, so do net share repurchases. This pattern suggests that, consistent with the spirit of our segmented-markets model, much of the variation in the two series comes from changes over time in the appeal of using the former to finance the

Figure 8 – Credit-Market Sentiment and Changes in Financing Mix, 1952–2015



Note: The left panel depicts the relationship between the change in net equity issuance (as a percent of the beginning-of-period book-value of total assets) and the predicted values of Δs_t—the change in the Baa-Treasury spread from year $t-1$ to year t—from the auxiliary forecasting regression in column (2) of Table 5; the right panel depicts the same relationship for the change in net debt issuance.

latter.[23]

We now ask whether the movements in these two variables can be predicted in advance based on the state of credit-market sentiment. As a preview, the left panel of Figure 8 shows a scatter plot of changes in net equity issuance against our credit-sentiment measure, while the right panel depicts the same relationship for the change in net debt issuance. These simple plots clearly illustrate that a forecasted widening of credit spreads is associated with a subsequent deleveraging in the nonfinancial corporate sector—that is, an increase in equity issuance and a decrease in debt issuance.

These graphical relationships are formalized in Table 11. Here we report the results from regressions in which the change in both net equity issuance (ΔNEI) and net debt issuance (ΔNDI) in year t—both scaled by assets at the end of year $t-1$—is regressed on the predicted change in the credit spread $\Delta\hat{s}_t$, where, as in Table 5, $\Delta\hat{s}_t$ is based on three valuation indicators: the log of the high-yield share and the levels of the Baa-Treasury spread and the Treasury term spread, all measured at $t-2$. We also add a few controls to the regressions: the growth rate of real nonfarm

[23] Ma (2016) notes that the apparent structural break in the mid-1980s likely reflects the impact of the SEC's Rule 10b-18, which established safe harbor conditions that lowered the legal risk associated with share repurchases; see http://www.sec.gov/rules/final/33-8335.htm for further details.

Table 11 – Forecasting Changes in Financing Mix: Aggregate Data

Regressors	Dependent Variables: ΔNEI/A	Dependent Variables: ΔNDI/A
A. *Sample Period:* 1952–2015		
$\Delta\hat{s}_t$	0.973^{***}	-0.882^{**}
	(0.336)	(0.449)
r_t^M	-0.001	.
	(0.003)	
$\Delta i_t^{(10y)}$	.	-0.235^{***}
		(0.038)
Δy_t	-0.058^{*}	0.152^{***}
	(0.035)	(0.021)
R^2	0.262	0.443
Effect on ΔFMIX[a]	1.855^{**}	
B. *Sample Period:* 1985–2015		
$\Delta\hat{s}_t$	0.841^{**}	-0.794^{**}
	(0.399)	(0.363)
r_t^M	0.001	.
	(0.003)	
$\Delta i_t^{(10y)}$	.	-0.194^{***}
		(0.063)
Δy_t	-0.172^{***}	0.214^{***}
	(0.013)	(0.024)
R^2	0.490	0.490
Effect on ΔFMIX[a]	1.635^{**}	

Note: The dependent variables are $\Delta\text{NEI}_t/A_{t-1}$ and $\Delta\text{NDI}_t/A_{t-1}$, where NEI_t denotes net equity issuance in year t, NDI_t denotes net debt issuance in year t, and A_t is the book-value of total assets in the nonfinancial corporate sector at the end of year t. Regressors: $\Delta\hat{s}_t$ = predicted change in the Baa-Treasury spread; r_t^M = value-weighted stock market (log) return; $\Delta i_t^{(10y)}$ = change in the 10-year Treasury yield; and Δy_t = log-difference of real GDP in the nonfarm business sector. Specifications in the top panel also include a dummy variable for the SEC Rule 10b-18 (1982–2015). All specification include a constant (not reported) and are estimated jointly with their auxiliary forecasting equation for Δs_t by NLLS. The explanatory variables in the auxiliary forecasting equation for Δs_t are $\ln \text{HYS}_{t-2}$, s_{t-2}, and TS_{t-2}, where HYS_t denotes the fraction of debt that is rated as high yield (Greenwood and Hanson, 2013) and TS_t is the term spread. Heteroskedasticity- and autocorrelation-consistent asymptotic standard errors reported in parentheses are computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994): * $p < .10$; ** $p < .05$; and *** $p < .01$.

[a] The implied coefficient on the change in the corporate financing fix, $\Delta\text{FMIX}/A$, which is defined as the difference between the change in net equity issuance ($\Delta\text{NEI}/A$) and the change in net debt issuance ($\Delta\text{NDI}/A$), scaled by the beginning-of-period total assets.

business sector output Δy_t; the value-weighted return on the stock market r_t^M (for the equity issuance regression) and the change in the 10-year Treasury yield $\Delta i_t^{(10y)}$ (for the debt issuance regression). Note that all of these controls are contemporaneous with respect to changes in net equity and debt issuance.

As can be seen in the table, when credit-market sentiment is elevated in year $t-2$—that is, when $\Delta\hat{s}_t$ is positive—this is associated with both an increase in equity issuance and a decline in debt issuance in year t. This pattern holds over both the full sample period from 1952 to 2015, as well as the more recent period since the mid-1980s, suggesting that based on our sentiment proxy, we are able to predict two years ahead of time a pronounced shift in the corporate financing mix. This pattern is just what is envisioned by the simple model described in Appendix C.

It is worth being clear on the distinction between our results and those of Ma (2016). She shows that, for example, aggregate share repurchases are negatively related to contemporaneous credit spreads, a result that she also interprets in terms of a model similar to the one we have in mind. By contrast, our key explanatory variable is not the contemporaneous credit spread, but rather $\Delta\hat{s}_t$, the fitted value of the change in the spread based on time $t-2$ sentiment indicators. So again, what is striking here is our ability to forecast changes in the financing mix two years in advance, based on the premise that elevated sentiment at $t-2$ leads to a reversal in credit-market conditions and to an increase in the cost of credit at time t.

One potential concern with the results reported in Table 11 is that, given our reliance on aggregate data, we might be picking up a compositional effect. That is, it could be that our sentiment indicator $\Delta\hat{s}_t$ is not forecasting a change in the financing mix of any one firm, but rather a change in the relative scale of those firms that are primarily debt issuers versus those that are primarily equity issuers. To address this issue, in Table 12 we undertake a similar analysis using firm-level Compustat data. In particular, for a sample period from 1985 to 2015, we create a panel of all nonfinancial firms with a senior unsecured credit rating. In the first two columns of the table, we regress both their change in net equity issuance for year t and their change in net long-term debt issuance on $\Delta\hat{s}_t$, controlling for firm fixed effects as well as contemporaneous firm-level sales growth and stock returns. Because the panel specification weights all firms equally, it is not influenced by changes in the relative scale of firms and hence is immune to the sorts of compositional effects that could potentially be at play in the aggregate data.

As can be seen, the results from this firm-level panel are very similar to those from the aggregate time-series data. The coefficient on $\Delta\hat{s}_t$ is significantly positive for equity issuance and significantly negative for debt issuance. The economic magnitudes are also quite close to those from Table 11. Thus it appears that our sentiment indicator is indeed able to forecast a true firm-level change in the financing mix and is not simply picking up some sort of compositional effect.

In both Table 11 and the first two columns of Table 12, the coefficients on $\Delta\hat{s}_t$ are of roughly the same magnitude (and opposite sign) for net equity issuance and net debt issuance. At first glance, this might be taken as evidence of relatively complete substitution across the debt and equity markets, so that a representative firm that loses a dollar of debt finance when credit-market sentiment worsens simply makes it up in the equity market, with little implication for its investment behavior.

However, this interpretation may be too simplistic, as it ignores the potential for heterogeneity across firms. For example, it may be that when credit becomes more expensive, a large investment-

TABLE 12 – Forecasting Changes in Financing Mix: Firm-Level Data

	All Rated Firms[a]		High-Yield Firms[b]	
Regressors	ΔNEI/A	ΔNDI/A	ΔNEI/A	ΔNDI/A
$\Delta\hat{s}_t$	1.171***	−0.856**	0.858**	−1.964***
	(0.422)	(0.412)	(0.386)	(0.496)
$\Delta \ln Y_{jt}$	−0.011**	0.046***	−0.008	0.031***
	(0.005)	(0.005)	(0.006)	(0.008)
r_{jt}	0.011***	0.001	0.013***	−0.003
	(0.002)	(0.004)	(0.002)	(0.004)
R^2 (within)	0.006	0.006	0.007	0.004
Effect on ΔFMIX[c]	2.027***		2.823***	

NOTE: Sample period: annual data from 1985 to 2015. The dependent variables are $\Delta\text{NEI}_{jt}/A_{j,t-1}$ and $\Delta\text{NDI}_{jt}/A_{j,t-1}$, where NEI_{jt} denotes net equity issuance of firm j in year t, NDI_{jt} denotes net (long-term) debt issuance of firm j in year t, and A_{jt} is the book-value of total assets of firm j at the end of year t. Regressors: $\Delta\hat{s}_t$ = predicted change in the Baa-Treasury spread; $\Delta \ln Y_{jt}$ = log-difference of real sales of firm j; and r_{jt} = total (log) return of firm j. The explanatory variables in the auxiliary forecasting equation for Δs_t are $\ln \text{HYS}_{t-2}$, s_{t-2} and TS_{t-2}, where HYS_t denotes the fraction of debt that is rated as high yield (Greenwood and Hanson, 2013) and TS_t is the term spread. All specifications includes firm fixed effects and are estimated by OLS. Heteroskedasticity- and autocorrelation-consistent asymptotic standard errors reported in parentheses are computed according to Driscoll and Kraay (1998): * $p < .10$; ** $p < .05$; and *** $p < .01$.

[a] No. of firms = 1,844; $\bar{T}_j = 8.6$ (years); and Total obs. = 15,895.

[b] No. of firms = 1,382; $\bar{T}_j = 5.7$ (years); and Total obs. = 7,811.

[c] The implied coefficient on the change in the corporate financing fix, ΔFMIX, which is defined as the difference between the change in net equity issuance (ΔNEI/A) and the change in net debt issuance (ΔNDI/A), scaled by the beginning-of-period total assets.

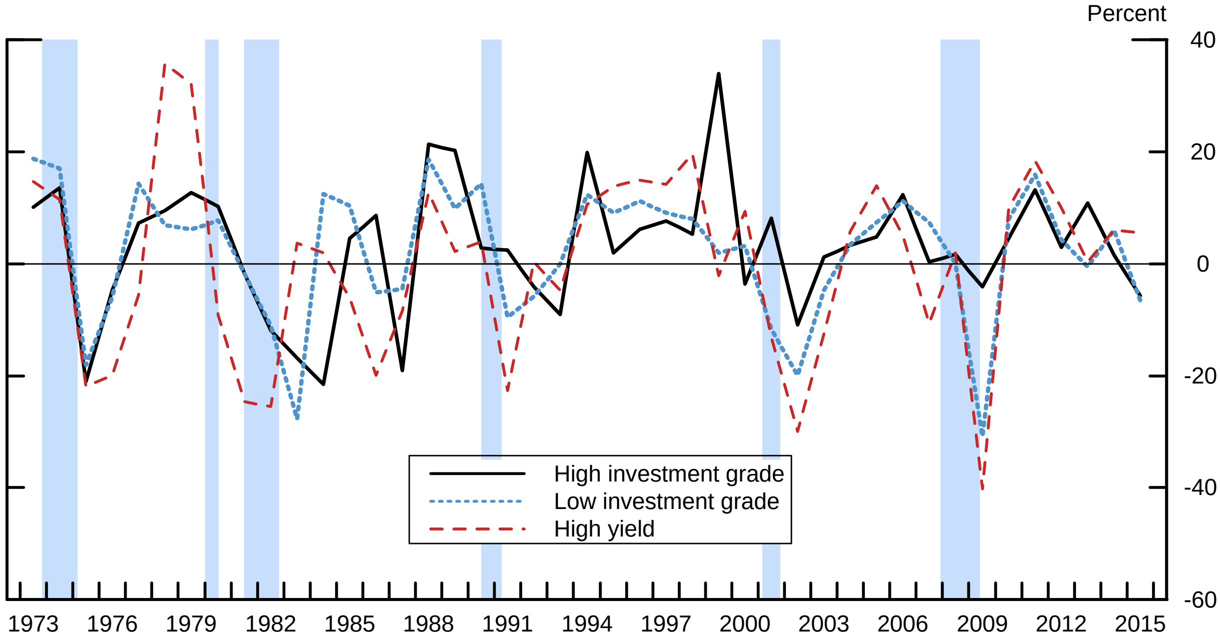
grade firm with a very flexible balance sheet and investment fixed at the first-best level trims its borrowing by \$1 and cuts its share repurchase activity by \$2, so that net equity issuance moves more than net debt issuance, while its investment is unaffected. At the same time, a junk-rated firm that is more financially constrained may cut its borrowing by \$1, increase its equity issuance by only \$0.50, and therefore be forced to cut investment by \$0.50 as well. For non-public firms without access to the equity market, as well as for households, the entire impact of a decline in borrowing may fall on their investment or consumption activity.

The latter two columns in Table 12 present evidence that is consistent with this heterogeneity-based hypothesis. Focusing now on the subsample of firms with a high-yield senior unsecured rating, we find that—in contrast to the aggregated results—a predicted reversal of credit-market sentiment has more than twice as large an impact on net debt issuance as on net equity issuance. In other words, for these lower-rated firms, the substitution between debt and equity markets does not appear to be complete, leaving more scope for their investment to be affected.

4.2 Investment Behavior of Firms by Rating Category

Finally, we turn to a comparison of the investment behavior of firms in different credit-rating categories. To do so, we use Compustat data on nonfinancial firms with senior unsecured credit

FIGURE 9 – Capital Expenditures by Type of Firm



NOTE: The solid line depicts the asset-weighted average growth rate of capital expenditures of nonfinancial Compustat firms that have, according to Moody's, a "high" investment-grade credit rating (i.e., Aaa, Aa1, Aa2, Aa3); the dotted line depicts the asset-weighted average growth rate of capital expenditures of nonfinancial Compustat firms that have a "low" investment-grade rating (i.e., A1, A2, A3, Baa1, Baa2, Baa3); and the dashed line depicts the asset-weighted average growth rate of capital expenditures of nonfinancial Compustat firms that have a "junk" rating (i.e., Ba1, Ba2, Ba3, B1, B2, B3, Caa1, Caa2, Caa3, Ca). Firms are sorted into the three credit-quality categories based on their credit rating at the beginning of each year; firm-level nominal capital expenditure data are deflated by the implicit price deflator for business fixed investment (2009 = 100). The shaded vertical bars denote the NBER-dated recessions.

ratings from 1973 to 2015 to run the following panel regression:

$$\Delta \ln I_{jt} = \sum_{k} \beta_k \Delta \hat{s}_t \times \mathbf{1}[\mathrm{RTG}_{j,t-1} = k] + \gamma_1 \Delta \ln Y_{jt} + \gamma_2 \Delta \ln Q_{j,t-1} + \eta_j + \epsilon_{jt}. \tag{5}$$

That is, we regress the change in the log of real capital expenditures for firm j in year t on: the predicted change in the credit spread $\Delta\hat{s}_t$; the log-difference in the firm's real sales $\Delta \ln Y_{jt}$; the lagged log-difference in the firm's Tobin's Q $\Delta \ln Q_{j,t-1}$; and firm fixed effects. To implement our test, we allow the coefficients on $\Delta\hat{s}_t$ to differ across three credit-quality buckets ($\mathrm{RTG}_{j,t-1}$): high yield (HY), low investment grade (low IG), and high investment grade (high IG).[24] Thus with this specification, we are asking whether elevated credit-market sentiment at time $t-2$ forecasts a more negative outcome for the time-t investment growth of firms with low credit ratings than for the time-t investment growth of firms with high credit ratings.

[24]The Moody's credit ratings—which are as of the end of year $t-1$—associated with the three groups are: high yield = Ba1, Ba2, Ba3, B1, B2, B3, Caa1, Caa2, Caa3, Ca; low investment grade = A1, A2, A3, Baa1, Baa2, Baa3; high investment grade = Aaa, Aa1, Aa2, Aa3.

Table 13 – Credit-Market Sentiment and Firm-Level Investment

	Dependent Variable: $\Delta \ln I_{jt}$	
Regressors	(1)	(2)
$\Delta\hat{s}_t \times \mathbf{1}[\mathrm{RTG}_{j,t-1} = \mathrm{HY}]$	-14.025^{***}	-7.103^{***}
	(3.724)	(2.409)
$\Delta\hat{s}_t \times \mathbf{1}[\mathrm{RTG}_{j,t-1} = \text{Low IG}]$	-11.503^{***}	-4.274^{**}
	(2.406)	(2.043)
$\Delta\hat{s}_t \times \mathbf{1}[\mathrm{RTG}_{j,t-1} = \text{High IG}]$	-3.610	1.062
	(2.663)	(3.165)
$\Delta \ln Y_{jt}$	.	0.853^{***}
		(0.030)
$\Delta \ln Q_{j,t-1}$	.	0.366^{***}
		(0.019)
R^2 (within)	0.009	0.144
$\Pr > W_{HY=HIG}$ [a]	0.013	0.021
$\Pr > W_{LIG=HIG}$ [b]	0.001	0.032

Note: Sample period: annual data from 1973 to 2015. Panel dimensions: No. of rated firms = 1,674; $\bar{T}_j$ = 10.5 (years); and Total obs. = 17,540. The dependent variable is $\Delta \ln I_{jt}$, the log-difference of real capital expenditures of firm j from year $t-1$ to year t. Regressors: $\Delta\hat{s}_t$ = predicted change in the Baa-Treasury spread; $\Delta \ln Y_{jt}$ = log-difference of real sales of firm j; and $\Delta Q_{j,t}$ = log-difference of Tobin's Q of firm j. $\Delta\hat{s}_t$ is interacted with $\mathbf{1}[\mathrm{RTG}_{j,t-1}]$, an indicator of the firm's credit quality at the end of year $t-1$. HY (high yield) = Ba1, Ba2, Ba3, B1, B2, B3, Caa1, Caa2, Caa3, Ca; Low IG (low investment grade) = A1, A2, A3, Baa1, Baa2, Baa3; and High IG (high investment grade) = Aaa, Aa1, Aa2, Aa3. The explanatory variables in the auxiliary forecasting equation for Δs_t are $\ln \mathrm{HYS}_{t-2}$, s_{t-2} and TS_{t-2}, where HYS_t denotes the fraction of debt that is rated as high yield (Greenwood and Hanson, 2013) and TS_t is the term spread. All specifications includes firm fixed effects and are estimated by OLS. Heteroskedasticity- and autocorrelation-consistent asymptotic standard errors reported in parentheses are computed according to Driscoll and Kraay (1998): * $p < .10$; ** $p < .05$; and *** $p < .01$.

[a] p-value of the Wald test of the null hypothesis that the coefficients on $\Delta\hat{s}_t$ are equal between the "HY" and "High IG" credit-risk categories.

[a] p-value of the Wald test of the null hypothesis that the coefficients on $\Delta\hat{s}_t$ are equal between the "Low IG" and "High IG" credit-risk categories.

The potential importance of the firm-level covariates can be seen in Figure 9, which plots the growth rate of aggregate capital expenditures of nonfinancial Compustat firms in each of the three credit-rating buckets. As can be seen in the figure, the investment growth of the lower-rated firms is considerably more procyclical than that of the most highly-rated firms. So when we attempt to measure the differential impact of credit-market sentiment on firms in different credit-rating categories, we want to do our best to control for any general tendency of lower credit-quality firms to be more exposed to the business cycle. To this end, we have experimented both with a more extensive set of firm-level controls, as well as with allowing the coefficients on each of these firm-level controls to also vary across the ratings buckets. However, none of these variations yields results materially different from those we report below.

The first column of Table 13 displays the coefficients on $\Delta\hat{s}_t$ by ratings bucket from a bare-bones specification that omits the firm-level controls. As can be seen, the differences across ratings buckets are economically large and of the predicted pattern. For example, in the high-yield bucket, the coefficient estimate implies that an increase of 100 basis points in credit-market sentiment at time $t-2$ is associated with a decline in the growth of capital expenditures for a typical firm of about 14.0 percentage points over the course of year t. By contrast, for low-investment grade firms, the corresponding estimate is 11.5 percentage points, and for high investment-grade firms, it is only 3.6 percentage points.

The second column of the table adds the firm-level controls. Not surprisingly, this reduces in absolute terms the coefficients on $\Delta\hat{s}_t$ across the board. In other words, some of the ability of credit-market sentiment to forecast declines in investment growth is soaked up by the fact that it also forecasts a contemporaneous decline in sales growth, which is itself strongly significant in explaining investment growth. Nevertheless, the significant differences between ratings categories in the effect of credit-market sentiment remain similar to the no-controls case. In particular, the impact of a 100-basis-point change in $\Delta\hat{s}_t$ is now 7.1 percentage points for a high-yield firm, 4.3 percentage points for a low investment-grade firm, and near zero for a high investment-grade firm. The evidence is thus broadly consistent with our basic cross-sectional hypothesis, which predicts that firms with lower credit ratings have investment behavior that is more sensitive to changes in aggregate credit-market sentiment.

5 Conclusions

This paper emphasizes the role of credit-market sentiment as an important driver of aggregate fluctuations in real activity. In so doing, it echoes an older narrative put forward by Minsky (1977, 1986) and Kindleberger (1978) and provides support for a new generation of behavioral models of the credit cycle such as Bordalo, Gennaioli, and Shleifer (2016), and Greenwood, Hanson, and Jin (2016). More specifically, we establish two basic findings about the importance of time-variation in the expected returns to credit-market investors. First, using almost a century of U.S. data, we show that when our sentiment proxies indicate that credit risk is being aggressively priced, this tends to be followed by a subsequent widening of credit spreads, and the timing of this widening is, in turn, closely tied to the onset of a contraction in economic activity.

Second, exploring the mechanism, we find that elevated credit-market sentiment forecasts a change in the composition of external finance: net debt issuance subsequently declines and net equity issuance increases. Thus, our proxy for credit-market sentiment appears to be able to predict a reduction in credit supply roughly two years in advance, especially for lower credit-quality firms. It seems likely that this reduction in credit supply is responsible for at least some of the decline in economic activity that occurs at around the same time.

There are a number of open questions that we have left unanswered. First, although we have provided some preliminary evidence on the mechanism by which changes in credit-market sentiment might impact the real economy, there is clearly much more to do here. In particular, how significant of a role do different types of financial intermediaries—commercial banks, broker-dealer firms, open-end bond funds, and so on—play in the transmission mechanism? One reason that this question is of interest is that to the extent that much of the credit intermediation takes place outside of the traditional banking sector, it will be harder for conventional forms of regulation to offset any of the undesirable effects of credit-market sentiment on economic activity.

Second, we are at an early stage in our understanding of what primitive factors drive fluctuations in credit-market sentiment. The behavioral models that we have discussed at length emphasize extrapolative beliefs, but in our empirical work, we have taken fluctuations in sentiment to be exogenous and so have not tested this aspect of the models, much less tried to pin down the precise nature of the extrapolative mechanism. Other work points to agency problems and reach-for-yield effects as the source of time-variation in expected credit returns, but we have not provided any new evidence on this score either. And one's view regarding the root source of credit-market sentiment clearly matters for how one thinks about policy implications. As just one example, consider the oft-debated question of whether monetary policy should concern itself with sentiment in financial markets. To answer this question in the affirmative, one would need to not only believe that fluctuations in sentiment matter for the real economy, but also to better understand the channels through which monetary policy impacts sentiment, perhaps working in conjunction with biases in beliefs. Fleshing all of this out to the point where one can give useful quantitative advice to policymakers will require a substantial amount of further work.

References

Adrian, T., and N. Boyarchenko (2013): "Intermediary Balance Sheets," Staff Report No. 651, Federal Reserve Bank of New York.

Adrian, T., E. Etula, and T. Muir (2014): "Financial Intermediaries and the Cross-Section of Asset Returns," *Journal of Finance*, 69(6), 2557–2596.

Baker, M., and J. Wurgler (2000): "The Equity Share in New Issues and Aggregate Stock Returns," *Journal of Finance*, 55(5), 2219–2257.

Barberis, N., A. Shleifer, and R. W. Vishny (1998): "A Model of Investor Sentiment," *Journal of Financial Economics*, 49(3), 307–343.

Baron, M. D., and W. Xiong (2016): "Credit Expansion and Neglected Crash Risk," Forthcoming *Quarterly Journal of Economics*.

Bassett, W. F., M. B. Chosak, J. C. Driscoll, and E. Zakrajšek (2014): "Changes in Bank Lending Standards and the Macroeconomy," *Journal of Monetary Economics*, 62(C), 23–40.

Belsley, D. A., E. Kuh, and R. E. Welsch (1980): *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity*. Wiley Series in Probability and Statistics, John Wiley & Sons Inc.

Bernanke, B. S. (1990): "On the Predictive Power of Interest Rates and Interest Rate Spreads," *New England Economic Review*, November/December, 51–68.

Bernanke, B. S., and M. Gertler (1989): "Agency Costs, Net Worth, and Business Fluctuations," *American Economic Review*, 79(1), 14–31.

Bordalo, P., N. Gennaioli, and A. Shleifer (2016): "Diagnostic Expectations and Credit Cycles," Working Paper, Dept. of Economics, Harvard University.

Borio, C., and H. Zhu (2012): "Capital Regulation, Risk-Taking and Monetary Policy: A Missing Link in the Transmission Mechanism," *Journal of Financial Stability*, 8(4), 236–251.

Brunnermeier, M., and L. H. Pedersen (2009): "Market Liquidity and Funding Liquidity," *Review of Financial Studies*, 22(6), 2201–2238.

Brunnermeier, M. K., and Y. Sannikov (2014): "A Macroeconomic Model with a Financial Sector," *American Economic Review*, 104(2), 379–421.

Cochrane, J. H. (2007): "The Dog Did Not Bark: A Defense of Return Predictability," *Review of Financial Studies*, 21(4), 1533–1575.

——— (2011): "Presidential Address: Discount Rates," *Journal of Finance*, 66(4), 1547–1608.

Cutler, D. M., J. M. Poterba, and L. H. Summers (1990): "Speculative Dynamics and the Role of Feedback Traders," *American Economic Review, Papers and Proceedings*, 80(2), 63–68.

Danielsson, J., H. S. Shin, and J.-P. Zigrand (2011): "Balance Sheet Capacity and Endogenous Risk," Discussion Paper No. 665. Financial Markets Group, London School of Economics & Political Science.

Dávila, E., and A. Korinek (2016): "Fire-Sale Externalities," NBER Working Paper No. 22444.

Driscoll, J. C., and A. Kraay (1998): "Consistent Covariance Matrix Estimation with Spatially Dependent Data," *Review of Economics and Statistics*, 80(4), 549–560.

Eggertsson, G. B., and P. Krugman (2012): "Debt, Deleveraging, and the Liquidity Trap: A Fisher-Minsky-Koo Approach," *Quarterly Journal of Economics*, 127(3), 1469–1513.

Fama, E. F. (1981): "Stock Returns, Real Activity, Inflation and Money," *American Economic Review*, 71(4), 545–565.

Fama, E. F., and K. R. French (1988): "Dividend Yields and Expected Stock Returns," *Journal of Financial Economics*, 22(1), 3–25.

Farhi, E., and I. Werning (2016): "A Theory of Macroprudential Policies in the Presence of Nominal Rigidities," *Econometrica*, 85(5), 1645–1704.

Fischer, S., and R. C. Merton (1984): "Macroeconomics and Finance: The Role of the Stock Market," *Carnegie-Rochester Conference Series on Public Policy*, 21, 57–108.

Fisher, I. (1933): "The Debt-Deflation Theory of Great Depression," *Econometrica*, 1(4), 337–357.

Friedman, B. M., and K. N. Kuttner (1992): "Money, Income, Prices, and Interest Rates," *American Economic Review*, 82(3), 472–492.

——— (1993a): "Economic Activity and the Short-Term Credit Markets: An Analysis of Prices and Quantities," *Brookings Papers on Economic Activity*, 24(2), 193–283.

——— (1993b): "Why Does the Paper-Bill Spread Predict Real Economic Activity?," in *Business Cycles, Indicators, and Forecasting*, ed. by J. H. Stock, and M. W. Watson, pp. 213–254. University of Chicago Press.

——— (1998): "Indicator Properties of the Paper-Bill Spread: Lessons From Recent Experience," *Review of Economics and Statistics*, 80(1), 34–44.

Geanokoplos, J. (2009): "The Leverage Cycle," in *NBER Macroeconomics Annual*, ed. by D. Acemoglu, K. Rogoff, and M. Woodford, pp. 1–65. The University of Chicago, Chicago.

Gennaioli, N., A. Shleifer, and R. W. Vishny (2012): "Neglected Risks, Financial Innovation, and Financial Fragility," *Journal of Financial Economics*, 104(3), 452–468.

Gertler, M., and P. Karadi (2015): "Monetary Policy Surprises, Credit Costs, and Economic Activity," *American Economic Journal: Macroeconomics*, 7(1), 44–76.

Gertler, M., and C. S. Lown (1999): "The Information in the High-Yield Bond Spread for the Business Cycle: Evidence and Some Implications," *Oxford Review of Economic Policy*, 15(3), 132–150.

Gilchrist, S., V. Yankov, and E. Zakrajšek (2009): "Credit Market Shocks and Economic Fluctuations: Evidence From Corporate Bond and Stock Markets," *Journal of Monetary Economics*, 56(4), 471–493.

Gilchrist, S., and E. Zakrajšek (2012): "Credit Spreads and Business Cycle Fluctuations," *American Economic Review*, 102(4), 1692–1720.

Graham, J., M. T. Leary, and M. R. Roberts (2015): "A Century of Capital Structure: The Leveraging of Corporate America," *Journal of Financial Economics*, 118(3), 658–683.

Greenwood, R., and S. G. Hanson (2013): "Issuer Quality and Corporate Bond Returns," *Review of Financial Studies*, 26(6), 1483–1525.

Greenwood, R., S. G. Hanson, and L. Jin (2016): "A Model of Credit Market Sentiment," Harvard Business School Project on Behavioral Finance and Financial Stability, Working Paper No. 2016-02.

Greenwood, R., and A. Shleifer (2014): "Expectations of Returns and Expected Returns," *Review of Financial Studies*, 27(3), 714–746.

Guerrieri, V., and G. Lorenzoni (2015): "Credit Crises, Precautionary Savings, and the Liquidity Trap," Working Paper, University of Chicago.

Hall, R. E. (2011): "The Long Slump," *American Economic Review*, 101(2), 431–469.

Hamilton, J. D. (2016): "Why You Should Never Use the Hodrick-Prescott Filter," Working Paper, Dept. of Economics, University of California San Diego.

Hanson, S. G., and J. C. Stein (2015): "Monetary Policy and Long-Term Real Rates," *Journal of Financial Economics*, 115(3), 429–448.

He, Z., and A. Krishnamurthy (2013): "Intermediary Asset Pricing," *American Economic Review*, 103(2), 732–770.

Hong, H., and J. C. Stein (1999): "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets," *Journal of Finance*, 54(6), 2143–2184.

Jiménez, G., S. Ongena, J.-L. Peydró, and J. Saurina (2014): "Hazardous Times for Monetary Policy: What do 23 Million Loans Say About the Impact of Monetary Policy on Credit Risk-Taking?," *Econometrica*, 82(2), 463–505.

Jordà, Ò., M. Schularick, and A. M. Taylor (2013): "When Credit Bites Back," *Journal of Money, Credit, and Banking*, 45(s2), 3–28.

Kashyap, A., J. C. Stein, and D. W. Wilcox (1993): "Monetary Policy and Credit Conditions: Evidence from the Composition of External Finance," *American Economic Review*, 83(1), 78–98.

Kindleberger, C. P. (1978): *Manias, Panics, and Crashes: A History of Financial Crises*. Basic Books, New York.

Kiyotaki, N., and J. H. Moore (1997): "Credit Cycles," *Journal of Political Economy*, 105(2), 211–248.

Koijen, R., M. Schmeling, and E. B. Vrugt (2015): "Survey Expectations of Returns and Asset Pricing Puzzles," Working Paper, Stern School of Business, New York University.

Korinek, A., and A. Simsek (2016): "Liquidity Trap and Excessive Leverage," *American Economic Review*, 106(3), 699–738.

Krishnamurthy, A., and T. Muir (2016): "Credit Spreads and the Severity of Financial Crises," Working Paper, Graduate School of Business, Stanford University.

Lettau, M., and S. Ludvigson (2001): "Consumption, Aggregate Wealth, and Expected Stock Returns," *Journal of Finance*, 56(3), 815–849.

Lian, C., Y. Ma, and C. Wang (2016): "Low Interest Rates and Risk Taking: Evidence from Individual Investment Decisions," Working Paper, Dept. of Economics, Harvard University.

Lorenzoni, G. (2008): "Inefficient Credit Booms," *Review of Economic Studies*, 75(3), 809–833.

Ma, Y. (2016): "Nonfinancial Firms as Cross-Market Arbitrageurs," Working Paper, Dept. of Economics, Harvard University.

Merton, R. C. (1974): "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates," *Journal of Finance*, 29(2), 449–470.

Mian, A. R., A. Sufi, and E. Verner (2016): "Household Debt and Business Cycles Worldwide," Working Paper, Booth School of Business, University of Chicago.

Minsky, H. P. (1977): "The Financial Instability Hypothesis: An Interpretation of Keynes and an Alternative to 'Standard' Theory," *Challenge*, 20(1), 20–27.

——— (1986): *Stabilizing an Unstable Economy*. Yale University Press, New Haven, CT.

Newey, W. K., and K. D. West (1987): "A Simple, Positive Semi-Definite, Heteroskedasticity- and Autocorrelation-Consistent Covariance Matrix," *Econometrica*, 55(3), 703–708.

——— (1994): "Automatic Lag Selection in Covariance Matrix Estimation," *Review of Economic Studies*, 61(4), 631–653.

Politis, D. N., and J. P. Romano (1994): "The Stationary Bootstrap," *Journal of the American Statistical Association*, 89(428), 1303–1313.

Rajan, R. G. (2006): "Has Finance Made the World Riskier?," *European Financial Management*, 12(4), 499–533.

Rognlie, M., A. Shleifer, and A. Simsek (2016): "Investment Hangover and the Great Recession," Working Paper, Dept. of Economics, Harvard University.

Schularick, M., and A. M. Taylor (2012): "Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crisis, 1870–2008," *American Economic Review*, 102(2), 1029–1061.

Shiller, R. J. (2000): "Measuring Bubble Expectations and Investor Confidence," *Journal of Psychology and Financial Markets*, 1(1), 49–60.

Shleifer, A., and R. W. Vishny (1992): "Liquidation Values and Debt Capacity: A Market Equilibrium Approach," *Journal of Finance*, 47(4), 1343–1366.

Simsek, A. (2013): "Belief Disagreements and Collateral Constraints," *Econometrica*, 81(1), 1–53.

Stein, J. C. (1996): "Rational Capital Budgeting in an Irrational World," *Journal of Business*, 69(4), 429–455.

——— (2012): "Monetary Policy as Financial-Stability Regulation," *Quarterly Journal of Economics*, 127(1), 57–95.

——— (2013): "Overheating in Credit Markets: Origins, Measurement, and Policy Responses," http://www.federalreserve.gov/newsevents/speech/stein20130207a.htm, Speech at the research symposium on "Restoring Household Financial Stability after the Great Recession: Why Household Balance Sheets Matter," Federal Reserve Bank of St. Louis, St. Louis MO, February 7, 2013.

——— (2014): "Incorporating Financial Stability Considerations into a Monetary Policy Framework," http://www.federalreserve.gov/newsevents/speech/stein20140321a.htm, Speech at the International Research Forum on Monetary Policy, Federal Reserve Board of Governors, Washington D.C., March 21, 2014.

Stock, J. H., and M. W. Watson (2003): "Forecasting Output and Inflation: The Role of Asset Prices," *Journal of Economic Literature*, 41(3), 788–829.

Appendices – For Online Publication

A Data Appendix

This appendix describes our data sources, as well as sample and variable constructions. FRED refers to the Federal Reserve Economic Data and ALFRED refers to the ArchivaL Federal Reserve Economic Data, two databases maintained by the research division of the Federal Reserve Bank of St. Louis. CRSP refers to the Center for Research in Security Prices.

A.1 U.S. Economic and Financial Data

Real Economic Activity: The data on real economic activity—as measured in the National Income and Product Accounts (that is, GDP, business fixed investment, residential investment, and consumer expenditures on durable goods)—are from FRED and are in billions of 2009 dollars. For the period 1929–1947, the data are available only at an annual frequency; from 1947 onward, they are available quarterly at a seasonally adjusted annual rate. For the 1948–2015 period, we converted each quarterly series to an annual frequency by averaging the series over the four quarters of each calendar year.

Unemployment: The data are from HAVER and are available at a monthly frequency since 1919. To construct changes in the unemployment rate at an annual frequency, we take December-to-December difference in the monthly series.

Population: To construct an estimate of real GDP per capita, we divide real GDP by total population (all ages, including armed forces overseas). Population data for the period 1919–1951 are available at an annual frequency (recorded as of July 1 of each year) from the U.S. Census Bureau Historical Data Release. From 1952 onward, the same series is available quarterly from FRED. We interpolated annual (July) data to monthly frequency using standard cubic spline methods. The resulting monthly data were then converted to an annual frequency by averaging the series over the 12 months of each calendar year. From 1952 onward, we converted the quarterly population series to an annual frequency by averaging the series over the four quarters of each calendar year.

Consumer Price Index: The data are from ALFRED and are available at a monthly frequency since 1913. To construct annual inflation, we calculate the December-to-December log-changes of the seasonally unadjusted monthly index (1982–84 = 100).

Moody's Yield on Baa-Rated Corporate Bonds: The data are from FRED and are available at a monthly (average) frequency since 1919. To convert the monthly series to annual frequency, we take the December value for each calendar year (thus, annual changes are calculated as December-to-December changes of the monthly series).

Yield on 10-year Treasury Securities: Constant-maturity yields are available at a monthly (average) frequency since 1920. To convert the monthly series to annual frequency, we take the December value for each calendar year (thus, annual changes are calculated as December-to-December changes of the monthly series).

Yield on 3-month Treasury Securities: The data are from FRED and are available at various frequencies (daily and weekly) since January 31, 1920. They are expressed on the discount basis. We first convert the 3-month discount rates to a semiannual bond basis (91-day convention) and the convert the resulting series to monthly frequency by taking the average of the available values for each month. To convert the monthly series to annual frequency, we take the December value for each calendar year (thus, annual changes are calculated as December-to-December changes of the monthly series).

Equity Market Indicators: The value-weighted total log return is from CRSP and is available at a daily frequency since 1927. To calculate annual returns, we cumulate the daily log returns in each calendar year. The corresponding annual dividend-price ratio is calculated as in Cochrane (2011). Annual log returns for the S&P 500 stock price index and the corresponding valuation measures are taken from "Online Data – Robert Shiller," available at http://www.econ.yale.edu/~shiller/data.htm. The equity share in new issues for the 1927–2010 period is taken from "Investor Sentiment Data (annual and monthly) 1934–2010," available at Jeffrey Wurgler's webpage http://www.people.stern.nyu.edu/jwurgler. Using the methodology described in Baker and Wurgler (2000), we extended the series through 2015.

High-Yield Share: The high-yield share—the fraction of gross bond issuance in the U.S. nonfinancial corporate sector that is rated as high yield by Moody's—for the 1926–2008 period is taken from Greenwood and Hanson (2013); using their methodology, we extended the series through 2015.

Bank Balance Sheets: The data on bank credit and loans for the 1914–1947 period are from the *Banking and Monetary Statistics*, published by the Board of Governors of the Federal Reserve System. The release contains principal assets and liabilities for banks that were members of the Federal Reserve System—virtually all commercial banks during this period—on call due dates. Our annual measure of bank credit (loans plus investments) and bank loans for the 1914–1947 period corresponds to their respective values as reported on the December 31 call report. From 1947 onward, bank credit and loans are from the Federal Reserve's weekly "Assets and Liabilities of Commercial Banks – H.8" statistical release.

Leverage: The data on aggregate leverage for the private nonfinancial sector, nonfinancial business sector, and the household sector are from the Federal Reserve's "Financial Accounts of the United States – Z.1" statistical release.

Corporate Financing Mix: Net debt issuance, net equity repurchases, and total assets for the U.S. nonfinancial corporate sector are from the Federal Reserve's "Financial Accounts of the United States – Z.1" statistical release. Net debt issuance is defined as total issuance minus debt reductions and net equity repurchase is defined as total equity repurchase minus total equity issuance.

A.2 Firm-Level Compustat Data

From the merged Compustat/CRSP database, we selected all nonfinancial firms, excluding firms in the following 2- or 3-digits NAICS sectors: 22 (Utilities); 491 (Postal Service); 52 (Finance & Insurance); 61 (Educational Services); 92 (Public Administration); and 99 (Unclassified). The resulting sample of firms was merged with the Moody's Default and Recovery Database (DRD), which contains credit-rating history for all corporate issuers rated by Moody's. Specifically, we matched the Moody's unique issuer identifiers (MAST_ISSR_NUM) to base CUSIPs in the merged Compustat/CRSP database.

Firm-level variables are defined as follows:

- Net equity issuance (NEI_{jt}) is from the Statement of Cash Flows and is defined as funds received from issuance of common and preferred stock (Compustat annual data item #108).
- Net debt issuance (NDI_{jt}) is from the Statement of Cash Flows and is defined as the amount of funds generated from issuance of long-term debt (Compustat annual data item #111).
- Real business investment (I_{jt}) is defined as nominal capital expenditures (Compustat annual data item #128) deflated by the implicit price deflator for business fixed investment (2009 = 100). Nominal capital expenditures correspond to cash outflows or funds used for additions to company's property, plant, and equipment, excluding amounts arising from acquisitions.
- Real sales (Y_{jt}) are defined as nominal sales (Compustat annual data item #12) deflated by the implicit GDP deflator for the U.S. nonfarm business sector (2009 = 100). Nominal sales correspond to gross sales (the amount of actual billings to customers for regular sales completed during the period) less cash discounts, trade discounts, returned sales, and allowances for which credit is given to customers.
- Tobin's Q (Q_{jt}) is defined as the book-value of total assets (Compustat annual data item #120), less the book-value of common equity (Compustat annual data item #60), plus the market-value of common equity from CRSP, divided by the book-value of total assets.
- Equity return (r_{jt}) is defined as the (total) log return during the firm's fiscal year. To construct annual returns, we cumulate the daily log returns from CRSP over the firm's fiscal year.

To ensure that our results were not influenced by a small number of extreme observations, we dropped from the sample all firm/year observations where the change in net equity issuance relative to assets ($\Delta\text{NEI}_{jt}/A_{j,t-1}$), the change in net debt issuance relative to assets ($\Delta\text{NDI}_{jt}/A_{j,t-1}$), the growth of real business investment ($\Delta \ln I_{jt}$), the growth of real sales ($\Delta \ln Y_{jt}$), or the growth in Tobin's Q ($\Delta \ln Q_{jt}$), was below the 2.5th or above the 97.5th percentile of its respective distribution. Table A-1 contains the selected summary statistics for the firm-level variables used in our analysis.

Table A-1 – Selected Characteristics of Rated Compustat Firms

Variable	Mean	StdDev	Min	Max
A. *Sample period*: 1985–2015[a]				
$\Delta\text{NEI}_{jt}/A_{j,t-1}$	−0.17	6.27	−40.80	54.14
$\Delta\text{NDI}_{jt}/A_{j,t-1}$	0.79	11.16	−31.62	44.86
B. *Sample period*: 1973–2015[b]				
$\Delta \ln I_{jt}$				
HY firms	3.67	51.85	−177.39	168.68
Low IG firms	3.04	35.12	−174.09	166.99
High IG firms	4.17	27.96	−147.10	132.25
All firms	3.40	42.61	−177.39	168.68
$\Delta \ln Y_{jt}$				
HY firms	6.16	18.93	−57.63	78.43
Low IG firms	3.99	14.41	−57.00	78.39
High IG firms	4.46	12.00	−55.31	72.69
All firms	4.95	16.36	−57.63	78.43
$\Delta \ln Q_{jt}$				
HY firms	−0.13	18.82	−80.46	68.80
Low IG firms	−0.16	16.86	−80.54	67.27
High IG firms	−0.71	16.42	−72.61	68.70
All firms	−0.19	17.68	−80.54	68.80

Note: All variables are expressed in percent; statistics are based on trimmed (P2.5/P97.5) data.

[a] No. of firms = 1,844; Total Obs. = 15,895.

[b] No. of HY firms = 1,262; No. of Low IG firms = 749; No. of High IG firms = 117; No. of firms = 1,674; Total Obs. = 17,540. Credit-rating categories (based on $t-1$ senior unsecured credit rating): HY (high yield) = Ba1, Ba2, Ba3, B1, B2, B3, Caa1, Caa2, Caa3, Ca; Low IG (low investment grade) = A1, A2, A3, Baa1, Baa2, Baa3; and High IG (high investment grade) = Aaa, Aa1, Aa2, Aa3.

B Additional Results

This appendix contains additional results, which are referenced in the main text.

Table B-1 – Stock-Market Sentiment and Economic Growth
(Full Sample Analysis)

	Dependent Variable: Δy_t			
Regressors	(1)	(2)	(3)	(4)
$\hat{r}_t^{SP}$	0.145**	.	0.010	.
	(0.057)		(0.046)	
$\hat{r}_t^{M}$	.	0.400	.	0.156
		(0.267)		(0.133)
R^2	0.332	0.353	0.306	0.335
	Auxiliary Regressions			
	r_t^{SP}	r_t^{M}	r_t^{SP}	r_t^{M}
$\ln[P/E10]_{t-2}$	−0.134***	.	.	.
	(0.036)			
$\ln[D/P]_{t-2}$	.	0.058**	.	.
		(0.029)		
$\ln \mathrm{ES}_{t-2}$	.	−0.035	.	.
		(0.025)		
$\ln[P/E10]_{t-1}$		.	−0.128***	.
			(0.037)	
$\ln[D/P]_{t-1}$	.	.	.	0.107**
				(0.047)
$\ln \mathrm{ES}_{t-1}$	.	.	.	−0.080**
				(0.038)
R^2	0.086	0.019	0.079	0.072

Note: Sample period: annual data from 1929 to 2015. The dependent variable is Δy_t, the log-difference of real GDP per capita from year $t-1$ to year t. Explanatory variables: $\hat{r}_t^{SP}$ = predicted S&P 500 (log) return; and $\hat{r}_t^{M}$ = predicted value-weighted stock market (log) return. Additional explanatory variables (not reported) include Δy_{t-1}. In the auxiliary return forecasting equations: $[P/E10]_t$ = cyclically adjusted P/E ratio for the S&P 500 (Shiller, 2000); ES_t = equity share in total (debt + equity) new external finance issuance (Baker and Wurgler, 2000); and $[D/P]_t$ = dividend-price ratio for the (value-weighted) stock market. All specifications include a constant (not reported) and are estimated jointly with their auxiliary return forecasting equation by NLLS. Heteroskedasticity- and autocorrelation-consistent asymptotic standard errors reported in parentheses are computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994): * $p < .10$; ** $p < .05$; and *** $p < .01$.

Table B-2 – Stock-Market Sentiment and Economic Growth
(Subsample Analysis)

	Dependent Variable: Δy_t					
Regressors	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{r}_t^{SP}$	0.066*	.	.	−0.066	.	.
	(0.036)		.	(0.055)	.	.
$\hat{r}_t^{M}$	.	0.068	0.033	.	−0.010	−0.004
		(0.065)	(0.030)		(0.027)	(0.041)
R^2	0.035	0.034	0.027	0.036	0.019	0.018
	Auxiliary Regressions					
	r_t^{SP}	r_t^{M}	r_t^{M}	r_t^{SP}	r_t^{M}	r_t^{M}
$\ln[P/E10]_{t-2}$	−0.108***	.	.	.	.	.
	(0.033)					
$\ln[D/P]_{t-2}$	.	0.088	.	.	.	.
		(0.077)				
$\ln \mathrm{ES}_{t-2}$	.	0.018	.	.	.	.
		(0.077)				
cay_{t-2}	.	.	3.124***	.	.	.
			(0.613)			
$\ln[P/E10]_{t-1}$	.	.	.	−0.108***	.	.
				(0.031)		
$\ln[D/P]_{t-1}$	.	.	.	.	0.225***	.
					(0.073)	
$\ln \mathrm{ES}_{t-1}$	.	.	.	.	−0.115	.
					(0.077)	
cay_{t-1}	.	.	.	.	.	2.786***
						(0.300)
R^2	0.079	0.058	0.135	0.080	0.149	0.112

Note: Sample period: annual data from 1952 to 2015. The dependent variable is Δy_t, the log-difference of real GDP per capita from year $t-1$ to year t. Explanatory variables: $\hat{r}_t^{SP}$ = predicted S&P 500 (log) return; and $\hat{r}_t^{M}$ = predicted value-weighted stock market (log) return. Additional explanatory variables (not reported) include Δy_{t-1}. In the auxiliary return forecasting equations: $[P/E10]_t$ = cyclically adjusted P/E ratio for the S&P 500 (Shiller, 2000); ES_t = equity share in total (debt + equity) new external finance issuance (Baker and Wurgler, 2000); $[D/P]_t$ = dividend-price ratio for the (value-weighted) stock market; and cay_t = consumption-wealth ratio (Lettau and Ludvigson, 2001). All specifications include a constant (not reported) and are estimated jointly with their auxiliary return forecasting equation by NLLS. Heteroskedasticity- and autocorrelation-consistent asymptotic standard errors reported in parentheses are computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994): * $p < .10$; ** $p < .05$; and *** $p < .01$.

TABLE B-3 – Predicting Credit-Market and Stock-Market Sentiment

	Dependent Variable			
Regressors	Δs_t	r_t^{SP}	Δs_t	r_t^{SP}
$\ln \text{HYS}_{t-2}$	0.098***	1.938*	0.103***	1.903*
	(0.035)	(1.054)	(0.027)	(1.012)
s_{t-2}	−0.219***	−0.809	−0.149***	−1.296
	(0.051)	(1.175)	(0.047)	(1.143)
TS_{t-2}	.	.	−0.141**	0.975
			(0.058)	(1.462)
$\ln[P/E10]_{t-2}$	0.002	−0.166***	0.002	−0.168***
	(0.002)	(0.035)	(0.001)	(0.034)
R^2	0.109	0.099	0.148	0.103

NOTE: Sample period: annual data from 1929 to 2015. The dependent variables are Δs_t, the change in the Baa-Treasury spread from year $t-1$ to year t and r_t^{SP}, the S&P 500 (log) return in year t. Regressors: HYS_t = fraction of debt that is rated as high yield (Greenwood and Hanson, 2013, the coefficient is multiplied by 100); s_t = Baa-Treasury spread; TS_t = term spread; and $[P/E10]_t$ = cyclically adjusted P/E ratio for the S&P 500 (Shiller, 2000). All specifications include a constant (not reported) and are estimated by OLS. Heteroskedasticity- and autocorrelation-consistent asymptotic standard errors reported in parentheses are computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994): * $p < .10$; ** $p < .05$; and *** $p < .01$.

Table B-4 – Credit-Market Sentiment and Economic Activity at Different Horizons
(Baseline Measures of Credit-Market Sentiment, 1929–2015)

	Forecast Horizon (years)		
	$h = 0$	$h = 1$	$h = 2$
A. *Dep. Variable: real GDP per capita*			
$\Delta\hat{s}_t$	-4.802^{***}	-5.436^{**}	-3.088
	(1.151)	(2.591)	(2.313)
Cumulative effect (pct.)[a]	-1.507^{***}	-3.213^{***}	-4.182^{**}
	(0.361)	(1.153)	(1.868)
B. *Dep. Variable: real business fixed investment*			
$\Delta\hat{s}_t$	-10.183^{***}	-9.569^{**}	-0.045
	(3.491)	(4.062)	(2.963)
Cumulative effect (pct.)	-3.196^{***}	-6.199^{***}	-6.213^{**}
	(1.095)	(2.306)	(3.050)
C. *Dep. Variable: real residential investment*			
$\Delta\hat{s}_t$	-12.381^{***}	-10.167^{*}	-0.352
	(3.704)	(5.235)	(5.814)
Cumulative effect (pct.)	-3.885^{***}	-7.076^{***}	-7.189^{**}
	(1.162)	(1.722)	(3.238)
D. *Dep. Variable: real durable goods consumption*			
$\Delta\hat{s}_t$	-6.402^{***}	-3.616	3.864
	(1.577)	(2.330)	(2.917)
Cumulative effect (pct.)	-2.009^{***}	-3.144^{***}	-1.931
	(0.495)	(0.706)	(1.378)
E. *Dep. Variable: unemployment rate*			
$\Delta\hat{s}_t$	2.316^{***}	2.288^{***}	1.670^{*}
	(0.579)	(0.738)	(0.936)
Cumulative effect (pps.)	0.707^{***}	1.405^{***}	1.915^{***}
	(0.177)	(0.393)	(0.673)

Note: Sample period: annual data from 1929 to 2015. In each panel, the dependent variable is Δy_{t+h}, the log-difference (simple difference in the case of the unemployment rate) in specified indicator of economic activity from year $t+h-1$ to year $t+h$. The entries denote the estimates of the coefficients associated with $\Delta\hat{s}_t$, the predicted change in the Baa-Treasury spread; additional explanatory variables (not reported) include Δy_{t-1}. The explanatory variables in the auxiliary forecasting equation for Δs_t are $\ln \mathrm{HYS}_{t-2}$ and s_{t-2} (see the main text for details). All specifications include a constant (not reported) and are estimated jointly with the auxiliary forecasting equation for Δs_t by NLLS. Heteroskedasticity- and autocorrelation-consistent asymptotic standard errors reported in parentheses are computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994): * $p < .10$; ** $p < .05$; and *** $p < .01$.

[a] The entries denote the estimated cumulative effect of a deterioration in credit-market sentiment from P25 to P75 of its historical distribution—a 30-basis-point increase in $\Delta\hat{s}_t$—on the specified measure of economic activity between $t-1$ and $t+h$.

Table B-5 – Credit-Market Sentiment and Economic Activity at Different Horizons (Alternative Measures of Credit-Market Sentiment, 1952–2015)

	Forecast Horizon (years)		
	$h = 0$	$h = 1$	$h = 2$
A. *Dep. Variable: real GDP per capita*			
$\Delta\hat{s}_t$	-2.490^{***}	-1.289^{**}	0.411
	(0.602)	(0.589)	(0.725)
Cumulative effect (pct.)[a]	-1.113^{***}	-1.689^{***}	-1.505^{**}
	(0.269)	(0.473)	(0.681)
B. *Dep. Variable: real business fixed investment*			
$\Delta\hat{s}_t$	-8.228^{***}	-6.546^{***}	-1.917
	(1.381)	(1.482)	(1.451)
Cumulative effect (pct.)	-3.677^{***}	-6.603^{***}	-7.460^{***}
	(0.617)	(1.061)	(1.366)
C. *Dep. Variable: real residential investment*			
$\Delta\hat{s}_t$	-17.418^{***}	-7.883^{*}	1.700
	(3.296)	(4.099)	(6.404)
Cumulative effect (pct.)	-7.784^{***}	-11.308^{***}	-10.548^{**}
	(1.473)	(2.539)	(4.297)
D. *Dep. Variable: real durable goods consumption*			
$\Delta\hat{s}_t$	-7.584^{***}	-2.294	4.190
	(2.069)	(1.667)	(2.671)
Cumulative effect (pct.)	-3.389^{***}	-4.415^{***}	-2.542
	(0.925)	(1.286)	(1.888)
E. *Dep. Variable: unemployment rate*			
$\Delta\hat{s}_t$	1.439^{***}	0.997^{***}	0.320
	(0.214)	(0.285)	(0.402)
Cumulative effect (pct.)	0.643^{***}	1.089^{***}	1.232^{***}
	(0.096)	(0.205)	(0.353)

Note: Sample period: annual data from 1952 to 2015. In each panel, the dependent variable is Δy_{t+h}, the log-difference (simple difference in the case of the unemployment rate) in specified indicator of economic activity from year $t + h - 1$ to year $t + h$. The entries denote the estimates of the coefficients associated with $\Delta\hat{s}_t$, the predicted change in the Baa-Treasury spread; additional explanatory variables (not reported) include Δy_{t-1}. The explanatory variables in the auxiliary forecasting equation for Δs_t are $\ln \mathrm{HYS}_{t-2}$, s_{t-2}, and TS_{t-2} (see the main for details). All specifications include a constant (not reported) and are estimated jointly with the auxiliary forecasting equation for Δs_t by NLLS. Heteroskedasticity- and autocorrelation-consistent asymptotic standard errors reported in parentheses are computed according to Newey and West (1987) with the automatic lag selection method of Newey and West (1994): * $p < .10$; ** $p < .05$; and *** $p < .01$.

[a] The entries denote the estimated cumulative effect of a deterioration in credit-market sentiment from P25 to P75 of its historical distribution—a 45-basis-point increase in $\Delta\hat{s}_t$—on the specified measure of economic activity between $t - 1$ and $t + h$.

C A Simple Model of Credit-Market Sentiment

The model that follows is adapted from Stein (1996), and it is also similar to that in Ma (2016). Consider a firm that can invest an amount I, which yields a net present value of $\theta f(I)$, where $f(I)$ is a concave function, and θ is a measure of the profitability of investment opportunities. The firm can finance the investment with either newly raised debt D or equity E, subject to the budget constraint that $I = D + E$. To capture the idea that there can be credit-market sentiment, we allow for the possibility that the credit spread on the debt deviates from its fundamental value by an amount δ; our sign convention here is that a positive value of δ represents debt that is expensive relative to a benchmark of frictionless financial markets and vice versa. For simplicity, we assume that equity is always fairly priced.

The firm also faces a cost of deviating from its optimal debt-to-capital ratio, which is denoted by d^*. This cost is assumed to be proportional to the scale of the firm and quadratic in the difference between d^* and the actual debt-to-capital ratio $d \equiv D/I$. Thus overall, the firm's problem is to choose the level of investment I and its capital structure d to maximize the following objective function:

$$\theta f(I) - \delta D - I\frac{\gamma}{2}\big(d - d^*\big)^2. \tag{C-1}$$

There are three terms in the objective function. The first term, $\theta f(I)$, is the net present value of investment. The second term, δD, is the relative cost associated with issuing debt as opposed to equity; this cost can be either positive or negative, depending on the sign of δ. And the third term, $I\frac{\gamma}{2}\big(d - d^*\big)^2$, is the cost associated with deviating from the optimal capital structure of d^*.

We can rewrite the firm's objective function as:

$$\theta f(I) - \delta d I - I\frac{\gamma}{2}\big(d - d^*\big)^2. \tag{C-2}$$

This yields the following first-order conditions with respect to I and d:

$$\theta f'(I) \;=\; \delta d + \frac{\gamma}{2}\big(d - d^*\big)^2; \tag{C-3}$$

$$d \;=\; d^* - \frac{\delta}{\gamma}. \tag{C-4}$$

Substituting equation (C-4) into equation (C-3) gives

$$\theta f'(I) = \delta d^* - \frac{\delta^2}{2\gamma}. \tag{C-5}$$

Equations (C-4) and (C-5) express the firm's choice of capital structure d and investment I as functions of the exogenous parameters. In so doing, they make clear the identification problem that arises in interpreting the results from Section 3. Suppose we know that elevated credit-market sentiment at time $t-2$ forecasts a decline in investment at time t. This could be either: (1) because the sentiment proxy is able to forecast a reduction in the appeal of future investment θ, as would be implied by a story where high levels of sentiment are associated with over-investment or mis-investment; or (2) because the sentiment proxy is able to forecast an increase in the future cost of borrowing δ. Based on observation of just investment I, one can see from equation (C-5) that these two hypotheses cannot be separated. However, equation (C-4) tells us that looking at the firm's financing mix can help in distinguishing between these two stories because the financing mix is unaffected by θ. Thus if both investment and the debt-to-capital ratio fall, this can only be explained by an increase in δ—that is, by an inward shift in the supply of credit. This motivates our first set of tests, which focus on relative movements in the aggregate net debt and net equity issuance of U.S. nonfinancial firms.

The model also suggests a set of cross-sectional tests. These come from noting that if our credit-sentiment proxy is able to forecast market-wide changes in the effective cost of credit, these changes should be more pronounced for lower credit-quality firms because such firms have, in effect, a higher loading on the aggregate market factor. In other words, the ratio of price-to-fundamentals falls by more for a Caa-rated issuer than for an Aa-rated issuer when market-wide sentiment deteriorates. Thus if firm i has a lower credit rating than firm j and we are predicting an increase in the market-wide spread δ, then we should also be predicting that δ_i will go up by more than δ_j. This implies that when credit-market sentiment is elevated at time $t-2$, we should expect that at time t firms with lower credit ratings will exhibit a larger drop in their investment; this can be seen explicitly in equation (C-5).