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ABSTRACT

Using U.S. data from 1929 to 2013, 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. That is, when our sentiment proxies indicate that credit risk is 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. 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, patterns 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 time-variation in expected returns to credit market investors can be an important driver of economic fluctuations.

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1 Introduction

Can "frothy" conditions in asset markets create risks to future macroeconomic performance? If so, which particular markets and measures of froth should receive the greatest attention from policymakers? And what exactly are the underlying channels of transmission?

In this paper, we attempt to shed some empirical light on the above questions. In doing so, we add to a large literature on the role of financial markets in business cycle fluctuations. However, our conceptual approach differs from much recent formal work in this area, in that we highlight the importance of time-variation in the expected returns to investors in credit markets and see these fluctuations in investor sentiment as a key driver of the cycle, rather than simply a propagation mechanism. By contrast, many of the modern theoretical models of the "financial accelerator" that have followed the seminal work of Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) are set in a simple efficient markets framework, in which the expected returns on all assets are constant, and there is time variation only in the cashflows associated with financial intermediation—that is, the process of intermediation is more efficient at some times than others, say because of greater availability of collateral. Our emphasis on the role of credit-market sentiment in the business cycle is thus closer in spirit to the narrative accounts of Minsky (1977) and Kindleberger (1978), who emphasize the potentially destabilizing nature of speculative movements in asset prices.[1]

We begin by documenting that measures of investor sentiment in the corporate bond market have significant predictive power for future economic activity. In particular, in U.S. data running from 1929 to 2013, we find 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 forecasts a substantial slowing of growth in real GDP, business investment, and employment over the subsequent few years. Thus buoyant credit-market sentiment today is associated with a significant weakening of real economic outcomes over a medium-term horizon.

This result appears to be connected to the existence of predictable mean reversion in credit-market conditions. That is, the following two relationships both hold: (1) when our sentiment proxies—namely, credit spreads and the junk share in issuance—indicate that credit risk is being aggressively priced, this tends to be followed by a subsequent widening of credit spreads; and (2) the timing of this increase in spreads is, in turn, closely linked to the onset of the decline in economic activity.

We couch these basic findings in terms of a two-step regression specification. In the first step, we use two-year lagged values of credits spreads and the junk share to forecast future *changes* in credit spreads. We then take the fitted values from this first-step regression, which we interpret as capturing fluctuations in credit-market sentiment, and use them in a second-step regression to predict changes in various measures of economic activity, including real GDP (per capita), real business fixed investment, and unemployment.[2]

[1] Recent work in a similar spirit includes Schularick and Taylor (2012); Jordà, Schularick, and Taylor (2013, 2014); Baron and Xiong (2014); Krishnamurthy and Muir (2015); Mian, Sufi, and Verner (2015); and Bordalo, Gennaioli, and Shleifer (2015).

[2] As described more fully below, the first- and second-step regressions are estimated jointly by nonlinear least

A simpler, one-step version of this approach is familiar from previous work. That earlier work has established that movements in credit spreads—as opposed to forecasted changes in credit spreads based on lagged valuation indicators—have substantial explanatory power for current and future economic activity.[3] Of course, results of this sort are open to a variety of causal interpretations. For example, 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. In particular, we show that a component of credit-spread changes that reflects not news about future cashflows, but rather an unwinding of past investor sentiment, still has strong explanatory power for future real activity.

Interestingly, the analogous two-step results do not hold for measures of stock-market sentiment. Thus while variables such as the dividend-price ratio, the cyclically-adjusted earnings-price ratio, and the equity share in total external finance have all been shown to forecast aggregate stock returns, we show that they have essentially no predictive power for real activity. In this specific sense, the credit market is fundamentally different from—and of potentially greater macroeconomic significance than—the stock market.

In quantitative terms, our full-sample (1929–2013) estimates indicate that when our measure of credit-market sentiment in year $t-2$ (that is, the fitted value of the year-t change in the credit spread) moves from the 25$^{\text{th}}$ to the 75$^{\text{th}}$ percentile of its historical distribution, this change is associated with a cumulative decline in real GDP growth (per capita) of about 3.0 percentage points over years t and $t+1$ and with a cumulative increase in the unemployment rate of about 1.2 percentage points over the same period. However, these full-sample estimates are disproportionately influenced by a few large outliers in the 1930s and 1940s. Using a post-war sample from 1952 to 2013 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 0.7 percentage points, respectively.

While our two-step econometric methodology closely resembles an instrumental-variables (IV) approach, we should emphasize that 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 an inward shift in credit supply, which, in turn, causes a contraction in economic activity. Now consider a natural alternative story: general investor over-optimism at time $t-2$ leads to economy-wide over-investment

squares, thus taking into account the fact that our credit-sentiment proxy is a generated regressor in the second-step regression.

[3] There is a long tradition in macroeconomics of using various sorts of credit spreads to forecast economic activity. For example, 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 financial asset prices to forecast economic activity.

and mal-investment, and it is this inefficient investment—for example, an excess supply of housing units or of capital in a particular sector—rather than anything having to do with credit supply, that sets the stage for a downturn beginning at time t. 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 first set of results that weighs decisively against this alternative hypothesis.

To make further progress on identifying a credit supply channel, there are two broad avenues that one can take. First, using just brute force, one can try to rule out some of the most obvious potential failures of the exclusion restriction. For example, one specific worry might be that when the credit markets are hot, nonfinancial firms lever up dramatically, and it is these increases in firm leverage—rather than any future changes in credit supply—that make the real economy vulnerable to future shocks. This particular story is one we can confront directly, by controlling for a variety of measures of firm leverage. When we do so, we find that our baseline results are unaffected. Of course, this still leaves open the possibility that there are other, harder-to-address alternatives, having to do with, say, the quality of aggregate investment during a credit boom, that we cannot address in this brute-force way.

A second approach is to flesh out the further implications of the credit supply channel for various aspects of firm financing activity, as opposed to just real-side behavior. We use a simple model to demonstrate that if a credit supply channel is at work, we should see additional patterns in the data that are not predicted by any obvious version of the alternative inefficient-investment hypothesis. For one, our sentiment proxies at time $t-2$ should not only predict changes in real activity beginning at time t, they should also predict a change in the *composition* of external finance. In particular, to the extent that credit supply has contracted, we should see a decrease in net debt issuance relative to net equity issuance.[4] 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 empirical 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.

Taken together, the story we have in mind is as follows. Heightened levels of sentiment in credit markets today portend bad news for future economic activity. This is because mean reversion implies that when sentiment is unusually positive today, it is likely to deteriorate in the future. Moreover, a sentiment-driven widening of credit spreads amounts to a reduction in the supply of credit, especially to lower credit-quality firms. It is this reduction in credit supply that exerts a negative influence on economic activity.

One important limitation of our empirical approach is that it treats time-varying investor sen-

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

timent in credit markets as exogenous. That is, nothing in our results explains why spreads might be unusually narrow today, or what it is that causes them to widen later on. With respect to the former, many observers have suggested that accommodative monetary policy, combined with a reaching-for-yield mechanism, can put downward pressure on credit-risk premiums.[5] If this is indeed the case, our results suggest that accommodative monetary policy may involve an intertemporal tradeoff: to the extent that policy compresses credit-risk premiums and thereby stimulates activity in the near term, it may also heighten the risk of a reversal in credit markets further down the road, with the accompanying contractionary impact on future activity. This potential mechanism deserves further research.

The remainder of the paper is organized as follows. In Section 2, we establish the basic macro results described above, focusing on both the full 1929–2013 period, as well as the less outlier-prone postwar sample of 1952 to 2013. In Section 3, we attempt to zero in on the economic mechanisms, and in particular, on the role of sentiment-induced shifts in the supply of credit. Doing so requires a simple model to guide our analysis and 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 4 discusses some policy implications of our findings, and Section 5 concludes.

2 Credit-Market Sentiment and the Macroeconomy

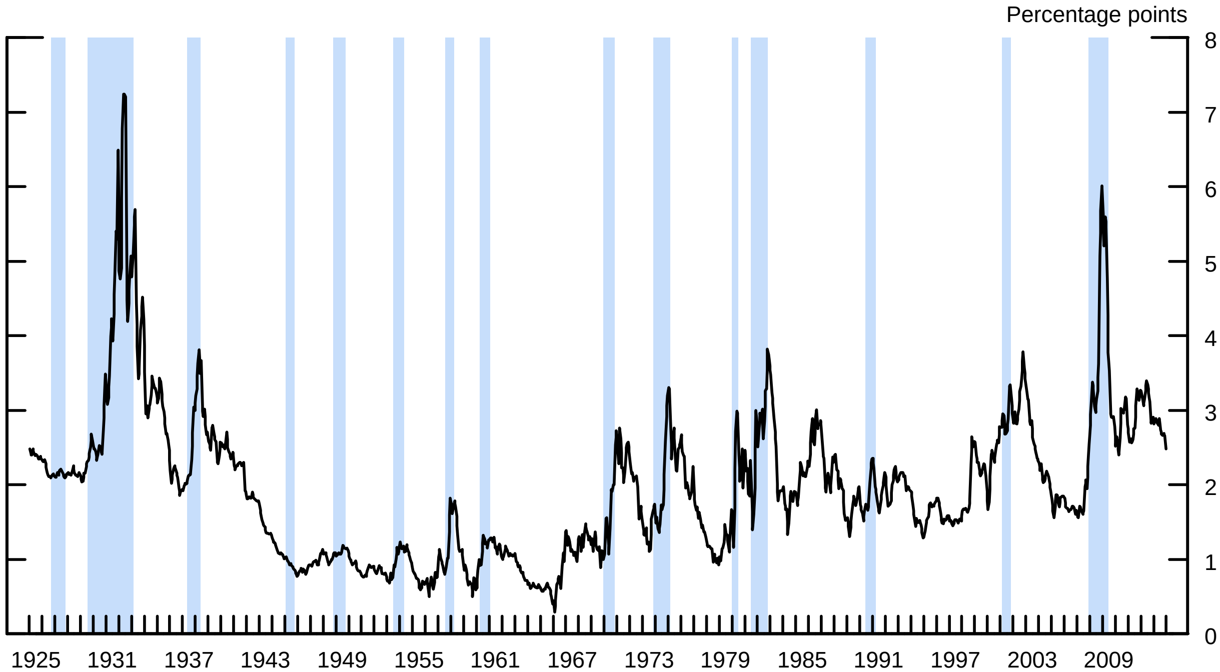
2.1 Measuring Credit-Market Sentiment

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 Appendix A.) Figure 1 plots this series over the period from 1925 to 2013. 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, in our baseline specifications, we forecast

[5] See, for example, Rajan (2006), Borio and Zhu (2008), and Stein (2013). Jiménez, Ongena, Peydró, and Saurina (2014) find that low policy rates are associated with an increased willingness of banks to take credit risk. With respect to the corporate bond market, Gertler and Karadi (2015) find that an easing of monetary policy reduces credit spreads; however, using a different approach, Gilchrist, López-Salido, and Zakrajšek (2015) do not find any impact of monetary policy on credit spreads.

Figure 1: Baa-Treasury Credit Spread



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

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, in an alternative specification, we add 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 2013, we also experiment with one other sentiment indicator: the excess bond premium (EBP) of Gilchrist and Zakrajšek (2012).[6] 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

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

Table 1: Credit Spreads, Stock Prices, and Economic Growth
(OLS Forecasting Regressions)

	Dependent Variable: Δy_{t+1}			
Regressors	(1)	(2)	(3)	(4)
Δs_t	-2.007^{***}	.	-1.569^{**}	-1.592^{**}
	(0.744)		(0.603)	(0.626)
r_t^M	.	0.090^{***}	0.055^{***}	0.054^{***}
		(0.020)	(0.017)	(0.018)
Δy_t	0.556^{***}	0.566^{***}	0.591^{***}	0.586^{***}
	(0.103)	(0.117)	(0.102)	(0.097)
$\Delta i_t^{(3m)}$	.	.	-0.646^{***}	-0.659^{***}
			(0.222)	(0.245)
π_t	.	.	.	0.027
				(0.075)
$\bar{R}^2$	0.501	0.504	0.536	0.531
Standardized effect on Δy_{t+1} [a]				
Δs_t	-0.371	.	-0.290	-0.294
r_t^M	.	0.379	0.230	0.227

NOTE: Sample period: annual data from 1929 to 2013. Δy_{t+1} is the log-difference of real GDP per capita from year t to year $t+1$. All specifications include a constant and dummy variables for WWII (1942–45) and the Korean War (1950–53), not reported, and are estimated by OLS. Explanatory variables: Δs_t = change in the Baa-Treasury spread; r_t^M = value-weighted stock market (log) return; $\Delta i_t^{(3m)}$ = change in the 3-month Treasury yield; and π_t = CPI inflation. 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) = 4.88 percent; StdDev(Δs_t) = 87 basis points; and StdDev(r_t^M) = 20.0 percent.

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 a handful of the most familiar predictor variables: the dividend-price ratio (Fama and French, 1988; Cochrane, 2007), the equity share in total external finance (Baker and Wurgler, 2000), and the cyclically-adjusted price-earnings ratio (Shiller, 2000). However, we have also experimented with a number of other predictors, with similar results.

2.2 Forecasting GDP 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+1}, the log-difference of real GDP per capita over the course of year $t+1$, using either changes in credit spreads or stock returns over the prior year t. More formally, we estimate variants of the following standard forecasting regression:

$$\Delta y_{t+1} = \beta_1 \Delta s_t + \beta_2 r_t^M + \boldsymbol{\gamma}' \mathbf{x}_t + \epsilon_{t+1}, \tag{1}$$

where Δs_t is the change in the Moody's Baa-Treasury credit spread over year t, r_t^M is the (total) log return on the value-weighted stock market over year t, and $\mathbf{x}_t$ is a vector of controls that includes the log-difference of real GDP per capita from year $t-1$ to t, the CPI inflation rate in year t, the change in the 3-month Treasury yield from year $t-1$ to t, and dummy variables for World War II (1942–45) and the Korean War (1950–53). The sample period runs from 1929 through the end of 2013.

In column (1) of the table, the explanatory variable of interest is Δs_t. As can be seen, changes in credit spreads have substantial forecasting power for future economic growth: a one standard deviation increase in credit spreads—almost 90 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 with r_t^M. In this simple exercise, the forecasting power of the stock market is strikingly similar to that of the corporate bond market: a one standard deviation increase in the broad stock market—about 20 percent—predicts an increase in the next year's real GDP growth per capita of 0.38 standard deviations.[7] In columns (3) and (4), we let Δs_t and r_t^M enter the regression together and also add two other explanatory variables, the change in the short-term Treasury yield ($\Delta i_t^{(3m)}$) and the inflation rate (π_t). In both cases, the horse race between credit spreads and stock returns appears to produce a virtual draw, with each of the two variables retaining statistically significant and economically similar predictive power for future output growth.

2.3 Financial-Market Sentiment and Economic Activity: 1929–2013

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

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

equations:

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

$$r_t^M = \boldsymbol{\theta}_2' \mathbf{z}_{2,t-1} + \nu_{2t}; \tag{3}$$

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

where $\Delta \hat{s}_t = \hat{\boldsymbol{\theta}}_1' \mathbf{z}_{1,t-2}$ and $\hat{r}_t^M = \hat{\boldsymbol{\theta}}_2' \mathbf{z}_{2,t-1}$. The first two forecasting regressions project current changes in credit spreads and stock returns on two- and one-year lagged valuation indicators, denoted by $\mathbf{z}_{1,t-2}$ and $\mathbf{z}_{2,t-1}$, respectively. 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).[8]

Table 2 presents our full-sample (1929–2013) 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).[9] As can be seen, the log of HYS_{t-2} enters with a significantly 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 0.095, so our valuation measures are reasonably powerful in predicting future movements in credit spreads. All of this is closely consistent with the results reported 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 and, if anything, larger than that obtained with OLS: the coefficient on $\Delta \hat{s}_t$ is -5.24, as compared to an OLS coefficient of -2.01 on Δs_t in column (1) of Table 1. 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 is our central result.

In column (2) of Table 2, we replace $\Delta \hat{s}_t$ with the fitted stock-market return, $\hat{r}_t^M$, and use lagged values of the log of the dividend-price ratio ($\log[D/P]_{t-1}$) and the log of the equity share ($\log \text{ES}_{t-1}$) as predictors for r_t^M. Note that these predictors for r_t^M are based on $t-1$ values, rather than the $t-2$ values that we used to predict Δs_t. We do this because when we use more distant

[8] 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).

[9] We also follow Greenwood and Hanson (2013) 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.

Table 2: Financial-Market Sentiment and Economic Growth

	Dependent Variable: Δy_t				
Regressors	(1)	(2)	(3)	(4)	(5)
$\Delta \hat{s}_t$	-5.237^{***}	.	.	-4.830^{***}	-5.004^{***}
	(1.449)			(1.027)	(1.385)
$\hat{r}_t^M$	.	0.155	.	0.081	.
		(0.145)		(0.113)	
$\hat{r}_t^{SP}$	.	.	0.132^{*}	.	0.058
			(0.072)		(0.062)
Δy_{t-1}	0.596^{***}	0.524^{***}	0.535^{***}	0.598^{***}	0.601^{***}
	(0.126)	(0.103)	(0.108)	(0.123)	(0.130)
R^2	0.398	0.342	0.336	0.404	0.402
	Auxiliary Forecasting Regressions				
	Δs_t	r_t^M	r_t^{SP}		
$\log \text{HYS}_{t-2}$	0.077^{***}	.	.		
	(0.026)				
s_{t-2}	-0.242^{***}	.	.		
	(0.038)				
$\log[D/P]_{t-1}$	.	0.105^{**}	.		
		(0.045)			
$\log \text{ES}_{t-1}$	.	-0.083^{**}	.		
		(0.039)			
$\log[P/\tilde{E}]_{t-1}$	.	.	-0.136^{***}		
			(0.039)		
R^2	0.095	0.072	0.086		

NOTE: Sample period: annual data from 1929 to 2013. The main dependent variable is Δy_t, the log-difference of real GDP per capita from year $t-1$ to year t. Explanatory variables: $\Delta \hat{s}_t$ = predicted change in the Baa-Treasury spread; $\hat{r}_t^M$ = predicted value-weighted stock market (log) return; and $\hat{r}_t^{SP}$ = predicted S&P 500 (log) return. Additional explanatory variables (not reported) include dummy variables for WWII (1942–45) and the Korean War (1950–53). 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); ES_t = equity share in total (debt + equity) new issues (Baker and Wurgler, 2000); $[D/P]_t$ = dividend-price ratio for the (value-weighted) stock market; and $[P/\tilde{E}]_t$ = 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 *** $p < .01$.

lags of stock-market sentiment indicators, our ability to forecast stock returns weakens significantly, and for our purposes, we are interested in giving the stock market the best possible opportunity to compete with the corporate bond market, even if this means stacking the deck somewhat in favor of the former. Nevertheless, even with this edge, the estimate of the effect of the expected stock market return $\hat{r}_t^M$ on output growth in year t is economically small and statistically insignificant.

In column (3), we use an alternative predictor for the stock market return, the log of the lagged cyclically-adjusted price-earnings ratio ($\log[P/\tilde{E}]_{t-1}$) for the S&P 500 stock price index (Shiller, 2000). For consistency, we also redefine the market return so that it is based on the S&P 500 index, rather than on the entire value-weighted market index. With this adjustment, the coefficient on the expected stock market return becomes marginally significant.[10] Finally, in columns (4) and (5), we run horse races by including fitted values of both Δs_t and r_t^M in the second-step regression simultaneously and forecasting each of them as before. Now the fitted change in the credit spread is the clear winner: its coefficient is almost identical to that from column (1), while the coefficients on the fitted stock market return are close to zero and statistically insignificant, regardless of the valuation indicators used to predict stock returns.

Thus, unlike the results in Table 1, those in Table 2 point to a sharp distinction between credit spreads and stock returns. While the two variables fare about equally well in simple OLS forecasting regressions, only changes in credit spreads predict output growth robustly when we take a two-step regression approach.[11] This divergence would seem to suggest that the forecasting power of the stock market for the macroeconomy arises primarily from its role as a passive predictor, rather than from any causal impact that the stock market has on the real economy. 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.

2.4 Outliers and Subsample Stability

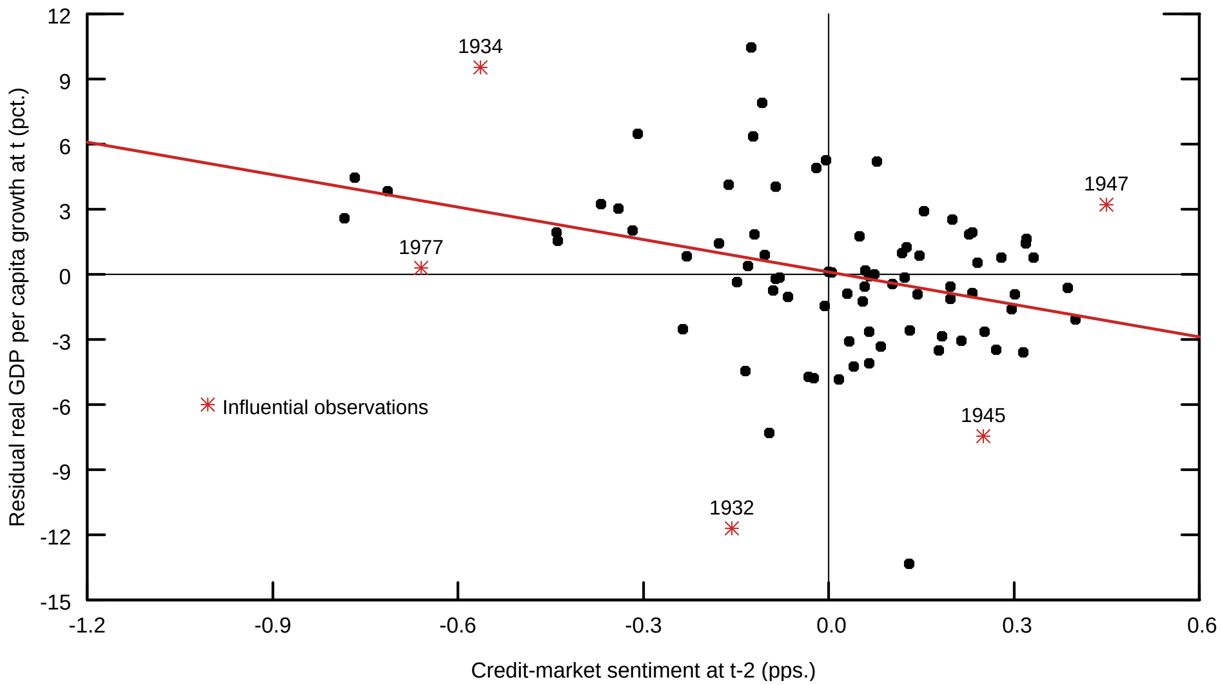
One might wonder to what extent the results in Table 2 are driven by a small number of disproportionately influential observations, for example, from the Great Depression or the recent Great Recession. We investigate this issue in a number of ways. To begin, Figure 2 provides a graphical illustration of the results in column (1) of Table 2. For each year in our full-sample period, we plot the residual value of real GDP growth per capita (obtained from a regression of GDP growth on the other covariates in the model) against the fitted value $\Delta\hat{s}_t$ from our first-step forecasting regression. 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 five 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 $\Delta\hat{s}_t$.

Four of these five overly-influential observations occur in the early years of the sample, in 1932, 1934, 1945, and 1947; 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.

[10] In unreported regressions, we have experimented with other predictors for future stock returns in the first-step regression, such as the consumption-wealth ratio (Lettau and Ludvigson, 2001). These too lead to insignificant estimates of the coefficient on fitted stock returns in the second stage.

[11] This divergence cannot be explained based on the first-step forecasting regressions for stock returns being less powerful than those for 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 forecasting power for real activity.

Figure 2: Credit-Market Sentiment and Economic Growth



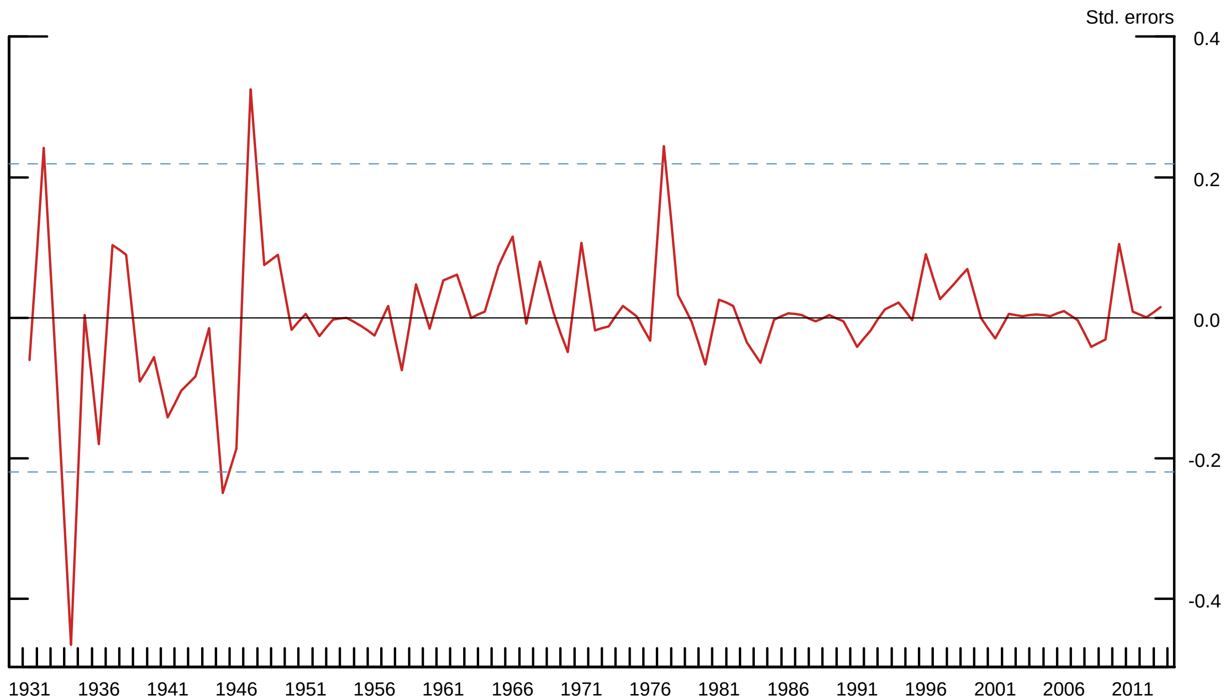
NOTE: The x-axis shows the predicted values of Δs_t—the change in the Baa-Treasury spread from year $t-1$ to year t—from the auxiliary forecasting regression in column (1) of Table 2. The y-axis shows the log-difference of real GDP per capita ($\times 100$) from $t-1$ to t after controlling for lagged dynamics, WWII, and the Korean War. See the text and Figure 3 for the definition of influential observations

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 4 makes this point in a somewhat different way. Here 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 quite choppy as the Great Depression and World War II years moved through the sample window—again, reflecting the large outliers in these years—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. 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, in Table 3 we create 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 2013, thereby excluding the portion of the sample that contains the most influential observations.

Figure 3: Influential Observations



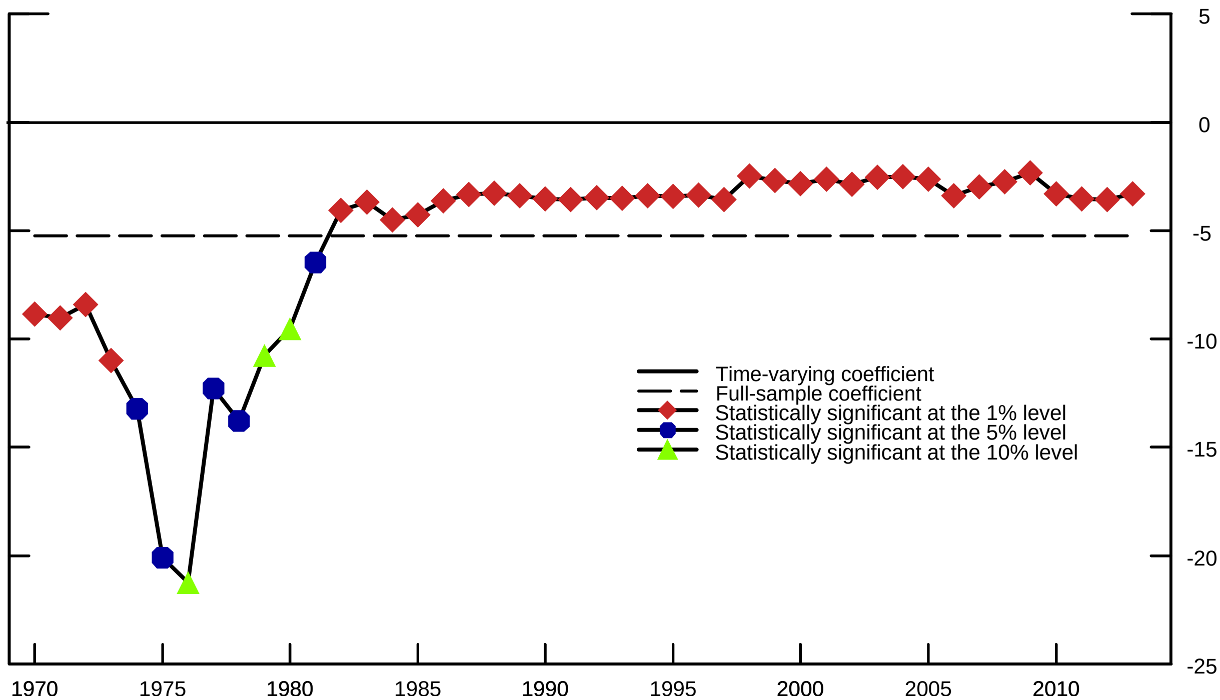
NOTE: The solid line depicts the time series of DFBETA statistics associated with the coefficient on $\Delta\hat{s}_t$ from Figure 2. The DFBETA statistic associated with observation $\tau = 1, 2 \ldots, T$ measures the change (in standard errors) in the OLS estimate of the coefficient on $\Delta\hat{s}_t$,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

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 -2.81 and -3.03, respectively, as compared to the full-sample value of -5.24. So while our full-sample findings are not simply the product of a few influential observations, it is clear that a handful of data points in the 1930s and 1940s do contribute to markedly larger (in absolute value) point estimates. In light of this fact, in much of what follows we use the shorter 1952–2013 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.

2.5 Different Horizons and Measures of Economic Activity

In Table 4, we extend the analysis in two directions, now focusing on the 1952–2013 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

Figure 4: Time-Varying Credit-Market Sentiment and Economic Growth



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 $\log \mathrm{HYS}_{t-2}$ and s_{t-2} (see the text for details).

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 in year $t+2$. Second, in the next two panels, we replace real GDP growth on the left-hand side of the regression, first with the growth of real business fixed investment and then with the change in the unemployment rate. The time profile and statistical significance of the estimates are broadly similar to those for output growth. In each case, we observe an effect that continues to accumulate over two years, before flattening out in the third year.

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, perhaps the most useful way to think about the magnitudes implied by the regression coefficients is in terms of a plausibly-sized shock to the fitted value $\Delta\hat{s}_t$. Thus for example, we can ask what the implications are for cumulative output 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 25$^{\text{th}}$ to the 75$^{\text{th}}$ percentile of its distribution, which corresponds to a roughly 28-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

Table 3: Financial-Market Sentiment and Economic Growth
(Subsample Analysis)

	Dependent Variable: Δy_t				
Regressors	(1)	(2)	(3)	(4)	(5)
A. *Sample Period:* 1952–2013					
$\Delta \hat{s}_t$	-2.805^{***}	.	.	-2.806^{***}	-2.704^{***}
	(0.557)			(0.545)	(0.610)
$\hat{r}_t^M$	.	-0.011	.	-0.013	.
		(0.027)		(0.026)	
$\hat{r}_t^{SP}$	.	.	0.069^{*}	.	0.016
			(0.036)		(0.044)
Δy_{t-1}	0.231	0.126	0.150	0.226	0.234
	(0.156)	(0.132)	(0.129)	(0.165)	(0.159)
R^2	0.104	0.018	0.033	0.106	0.105
B. *Sample Period*: 1952–2007					
$\Delta \hat{s}_t$	-3.031^{***}	.	.	-2.938^{***}	-3.166^{***}
	(0.702)			(0.789)	(0.982)
$\hat{r}_t^M$	.	-0.028	.	-0.023	.
		(0.031)		(0.026)	
$\hat{r}_t^{SP}$	.	.	0.031	.	-0.029
			(0.039)		(0.069)
Δy_{t-1}	0.126	0.034	0.063	0.109	0.118
	(0.126)	(0.134)	(0.127)	(0.143)	(0.142)
R^2	0.107	0.013	0.006	0.114	0.109

NOTE: The main dependent variable is Δy_t, the log-difference of real GDP per capita from year $t-1$ to year t. Explanatory variables: $\Delta \hat{s}_t$ = predicted change in the Baa-Treasury spread; $\hat{r}_t^M$ = predicted value-weighted stock market (log) return; and $\hat{r}_t^{SP}$ = predicted S&P 500 (log) return. See the text and notes to Table 2 for details regarding the auxiliary forecasting equations for Δs_t, r_t^M, 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 *** $p < .01$.

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 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 25^{th}-to-75^{th}-percentile change in credit-market sentiment as of $t-2$ forecasts a cumulative decline in real business fixed investment of almost 5.0 percentage points over the period t to $t+1$, and a cumulative increase in the unemployment rate of about 0.7 percentage points.[12]

[12] As emphasized above, these numbers are arguably on the conservative side, in that we get substantially larger economic effects if we calibrate based on the full 1929–2013 sample period. For example, in untabulated results, we find that the corresponding impacts on GDP and unemployment are 3.0 and 1.2 percentage points, respectively, in

Table 4: Credit-Market Sentiment and Economic Activity at Different Horizons

	Forecast Horizon (years)		
	$h = 0$	$h = 1$	$h = 2$
A. *Dep. Variable: real GDP per capita*			
$\Delta\hat{s}_t$	-2.890^{***}	-1.455^{**}	0.328
	(0.519)	(0.616)	(0.779)
Cumulative effect (pct.)[a]	-0.820^{***}	-1.233^{***}	-1.140^{**}
	(0.147)	(0.284)	(0.450)
B. *Dep. Variable: real business fixed investment*			
$\Delta\hat{s}_t$	-9.548^{***}	-7.601^{***}	-2.661
	(1.402)	(1.513)	(1.642)
Cumulative effect (pct.)	-2.709^{***}	-4.866^{***}	-5.621^{***}
	(0.398)	(0.697)	(0.943)
C. *Dep. Variable: unemployment rate*			
$\Delta\hat{s}_t$	1.573^{***}	1.002^{***}	0.201
	(0.336)	(0.293)	(0.374)
Cumulative effect (pps.)	0.446^{***}	0.731^{***}	0.788^{***}
	(0.095)	(0.160)	(0.252)

NOTE: Sample period: annual data from 1952 to 2013. In each system specification, the main dependent variables are 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 $\log \mathrm{HYS}_{t-2}$ 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 28-basis-point increase in credit market sentiment—a move in $\Delta\hat{s}_t$ from P25 to P75—on the specified measure of economic activity between $t - 1$ and $t + h$.

2.6 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 Greenwood and Hanson (2013)—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 2013, 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

the longer sample.

Table 5: Credit-Market Sentiment and Economic Growth
(Alternative Measures of Credit-Market Sentiment)

	Dependent Variable: Δy_t					
	1929–2013	1952–2013	1973–2013			
Regressors	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\hat{s}_t$	-4.232^{***}	-3.050^{***}	-3.524^{***}	-3.083^{***}	-3.212^{***}	-2.788^{***}
	(1.141)	(1.052)	(0.668)	(0.959)	(1.084)	(0.995)
Δy_{t-1}	0.554^{***}	0.123	0.501^{***}	0.334^{*}	0.517^{***}	0.376^{**}
	(0.111)	(0.148)	(0.151)	(0.182)	(0.137)	(0.168)
R^2	0.395	0.178	0.319	0.409	0.227	0.372
	Auxiliary Forecasting Regressions					
$\log \mathrm{HYS}_{t-2}$	0.090^{***}	0.125^{***}	0.105^{***}	0.129^{***}	.	.
	(0.030)	(0.043)	(0.019)	(0.042)		
s_{t-2}	-0.215^{***}	-0.087^{*}	-0.270^{***}	-0.182^{***}	.	.
	(0.040)	(0.050)	(0.080)	(0.040)		
TS_{t-2}	-0.112^{***}	-0.161^{***}	.	-0.155^{***}	.	-0.192^{***}
	(0.041)	(0.040)		(0.037)		(0.050)
EBP_{t-2}	.	.	.	.	-0.430^{***}	-0.427^{***}
					(0.138)	(0.086)
R^2	0.134	0.107	0.088	0.137	0.071	0.149

NOTE: The main dependent variable is Δy_t, the log-difference of real GDP per capita from year $t-1$ to year t. Explanatory variables: $\Delta\hat{s}_t$ = predicted change in the Baa-Treasury spread; for the 1929–2013 sample period, additional explanatory variables (not reported) include dummy variables for WWII (1942–45) and the Korean War (1950–53). 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 *** $p < .01$.

forecasting regression increases notably, from 0.095 to 0.134.

With this expanded set of variables, the estimate of the impact of $\Delta\hat{s}_t$ on Δy_t declines slightly in absolute magnitude, from -5.24 to -4.23. 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 (1952–2013) 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 2013; we do so because this even more recent period is the one over which we can compute the excess bond

Table 6: Credit-Market Sentiment and Economic Activity at Different Horizons
(Alternative Measures of Credit-Market Sentiment)

	Forecast Horizon (years)		
	$h = 0$	$h = 1$	$h = 2$
A. *Dep. Variable: real GDP per capita*			
$\Delta\hat{s}_t$	-3.206^{***}	-1.612^{***}	0.601
	(1.078)	(0.608)	(0.800)
Cumulative effect (pct.)[a]	-1.492^{***}	-2.244^{***}	-1.964^{***}
	(0.502)	(0.658)	(0.627)
B. *Dep. Variable: real business fixed investment*			
$\Delta\hat{s}_t$	-10.210^{***}	-9.743^{***}	-2.628
	(2.127)	(1.445)	(2.540)
Cumulative effect (pct.)	-4.753^{***}	-9.288^{***}	-10.512^{***}
	(0.990)	(1.507)	(1.649)
C. *Dep. Variable: unemployment rate*			
$\Delta\hat{s}_t$	2.182^{***}	1.606^{***}	0.195
	(0.662)	(0.305)	(0.474)
Cumulative effect (pps.)	1.016^{***}	1.763^{***}	1.854^{***}
	(0.308)	(0.356)	(0.337)

NOTE: Sample period: annual data from 1952 to 2013. In each system, the main dependent variables are 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 $\log \text{HYS}_{t-2}$, s_{t-2}, and TS_{t-2} (see the text and notes to Table 5 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 47-basis-point increase in credit market sentiment—a move in $\Delta\hat{s}_t$ from P25 to P75—on the specified measure of economic activity between $t-1$ and $t+h$.

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 6, which covers the sample period from 1952 to 2013 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 25$^{\text{th}}$ to the 75$^{\text{th}}$ percentile of its historical distribution is now 47 basis points instead of 28 basis points. This implies a decline in real GDP growth of 2.2 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 0.7 percentage points to 1.8 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.

2.7 Controlling for Nonfinancial Leverage

As noted above, our two-step methodology should not be thought of as an IV estimation strategy because of what is effectively an exclusion-restriction violation: the possibility remains that our credit-market sentiment variables influence economic activity not via their impact on future changes in credit supply, but through some other channel. Although we can never directly rule out all potential stories along these lines, we can investigate some of the more obvious possibilities. For example, one natural hypothesis is that when the credit market is buoyant and junk bond issuance is running at high levels, the leverage of operating firms is rising, and it is this increased leverage, rather than any change in future credit supply, that makes the real economy more vulnerable to future shocks.

Table 7 presents some results that bear on this hypothesis. In the top panel of the table, which cover the sample period 1929–2012, we draw on recent work by Graham, Leary, and Roberts (2014) (GLR hereafter), who construct several historical time series of corporate leverage.[13] We begin in column (1) with our two-step specification from column (1) of Table 5 (which includes the term spread as a predictor in the first-step regression), and add to the second-step regression the year $t-2$ change in the log of GLR's measure of long-term debt to book assets ($[\mathrm{LTD/A}]_t$) for the aggregate nonfinancial corporate sector. In column (2) we take a similar approach, but use instead GLR's series for total debt to book assets ($[\mathrm{TD/A}]_t$), while in column (3), we use their broader measure of total liabilities to assets ($[\mathrm{TL/A}]_t$). In all three cases, we obtain a similar result: the coefficients on the change-in-leverage proxies are completely insignificant, and our estimates of the coefficient on $\Delta\hat{s}_t$ are virtually unchanged from their value of -4.23 reported in column (1) of Table 5. In further results (not reported), we find that nothing is altered if we instead enter the GLR leverage variables in log levels, rather than in changes, or use multiple lags of leverage and let the regression pick the extent of differencing.

Although these results are comforting, it might be argued that they do not represent a particularly stringent test. It may well be that the financial fragility of the nonfinancial corporate sector is not well summarized by aggregate leverage, but rather by the leverage of the most vulnerable firms. Moreover, it could be that when credit-market sentiment is elevated, it is these vulnerable firms in particular that are most prone to increasing their borrowing.

[13] We are grateful to John Graham, Mark Leary, and Michael Roberts for sharing their historical data on corporate leverage with us.

Table 7: Credit-Market Sentiment, Leverage, and Economic Growth

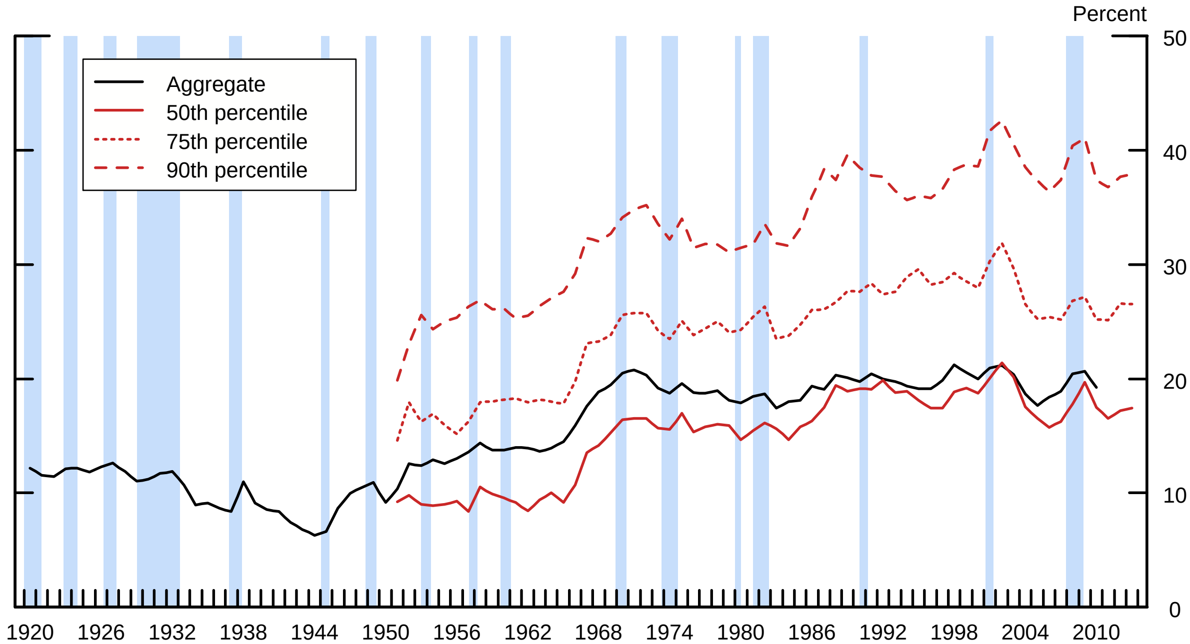
	Dependent Variable: Δy_t		
Regressors	(1)	(2)	(3)
A. *Aggregate Leverage Measures* (1929–2012)			
$\Delta\hat{s}_t$	-4.315^{***}	-4.320^{***}	-4.306^{***}
	(1.155)	(1.108)	(1.121)
$\Delta\log[\text{LTD/A}]_{t-2}$	0.006	.	.
	(0.029)		
$\Delta\log[\text{TD/A}]_{t-2}$	.	0.006	.
		(0.029)	
$\Delta\log[\text{TL/A}]_{t-2}$	.	.	−0.022
			(0.085)
R^2	0.397	0.396	0.397
B. *Cross-Sectional Percentiles of Leverage* (1952–2013)			
$\Delta\hat{s}_t$	-3.050^{***}	-3.063^{***}	-3.056^{***}
	(1.043)	(1.019)	(1.084)
P50: $\Delta\log[\text{LTD/A}]_{t-2}$	−0.000	.	.
	(0.037)		
P75: $\Delta\log[\text{LTD/A}]_{t-2}$	.	−0.025	.
		(0.051)	
P90: $\Delta\log[\text{LTD/A}]_{t-2}$	.	.	0.034
			(0.038)
R^2	0.178	0.182	0.184

NOTE: The main dependent variable is Δy_t, the log-difference of real GDP per capita from year $t-1$ to year t. Explanatory variables: $\Delta\hat{s}_t$ = predicted change in the Baa-Treasury spread and growth in various measures of corporate leverage: $[\text{LTD/A}]_t$ = long-term debt to assets; $[\text{TD/A}]_t$ = total debt to assets; and $[\text{TL/A}]_t$ = total liabilities to assets. Specifications in Panel A also include Δy_{t-1} and dummy variables for WWII (1942–45) and the Korean War (1950–53), while those in the Panel B include Δy_{t-1} (not reported). Measures of aggregate leverage are from Graham, Leary, and Roberts (2014), while P50, P75, and P90 denote the (sales-weighted) 50th, 75th, and 90th cross-sectional percentiles, respectively, of the long-term debt to assets ratio ($[\text{LTD/A}]_t$) calculated from firm-level Compustat data. The explanatory variables in the auxiliary forecasting equation for Δs_t are $\log \text{HYS}_{t-2}$, 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 *** $p < .01$.

To address this possibility, we need more disaggregated data on firm balance sheets, so we work with Compustat data over the shorter period from 1952 to 2013.[14] In an effort to capture the balance sheet positions of relatively vulnerable firms, we compute for each year the ratio of long-term debt to assets at the 50$^{\text{th}}$, 75$^{\text{th}}$, and 90$^{\text{th}}$ percentiles of the (sales-weighted) cross-sectional distribution of nonfinancial firms. Then, in the lower panel of Table 7, we replicate the analysis from column (1) of the upper panel, now controlling for changes in these alternative proxies for leverage. As can be seen, a similar result emerges: none of the leverage controls has any appreciable impact

[14]Standard & Poor's Financial Services LLC ("S&P"), Compustat.

Figure 5: Corporate Leverage



NOTE: The solid black line depicts the ratio of long-term debt to (book) assets for the U.S. nonfinancial corporate sector from Graham, Leary, and Roberts (2014). The red lines depict the (sales-weighted) cross-sectional percentiles (P50 = solid; P75 = dotted; P90 = dashed) of the ratio of long-term debt to (book) assets calculated using the Compustat firm-level data. The shaded vertical bars denote the NBER-dated recessions.

on our estimate of the coefficient on $\Delta\hat{s}_t$; in all cases this coefficient is very close to its benchmark value of -3.05 from column (2) of Table 5, which is estimated over the same sample period 1952 to 2013.

Figure 5 provides some partial intuition for these findings. The figure shows that the measures of corporate leverage that we examine are generally much smoother than the credit spread series. The GLR series for aggregate leverage has some low frequency time trends but little discernible business cycle variation. And while the more skewed 75^{th} and 90^{th} percentile leverage series do appear to have some co-movement with the business cycle, they have much less in the way of high-frequency variation than do credit spreads. For example, there is a small run-up in the leverage of firms at the 90^{th} percentile of the distribution in the few years leading up to the recent financial crisis, but this run-up looks small in comparison to the overall time trend in the same variable.

2.8 Controlling for Bank Credit Growth

In recent work, Schularick and Taylor (2012) and Jordà, Schularick, and Taylor (2013) 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, a hypothesis clearly similar in spirit to ours, albeit more focused on credit extended via

Table 8: Credit-Market Sentiment, Bank Balance Sheets, and Economic Growth

	Dependent Variable: Δy_t			
Regressors	(1)	(2)	(3)	(4)
A. *Sample Period:* 1929–2013				
$\Delta\hat{s}_t$	.	.	-2.986^{***}	-4.817^{***}
			(0.697)	(1.835)
$\Delta_5 \log \mathrm{BC}_{t-1}$	-0.489^{**}	.	-0.372^{*}	.
	(0.215)		(0.215)	
$\Delta_5 \log \mathrm{BL}_{t-1}$	.	-0.143^{**}	.	0.065
		(0.064)		(0.085)
R^2	0.393	0.333	0.430	0.399
B. *Sample Period:* 1952–2013				
$\Delta\hat{s}_t$	.	.	-3.361^{***}	-3.424^{***}
			(1.214)	(1.300)
$\Delta_5 \log \mathrm{BC}_{t-1}$	0.060	.	0.153	.
	(0.200)		(0.173)	
$\Delta_5 \log \mathrm{BL}_{t-1}$	.	-0.009	.	0.163
		(0.079)		(0.152)
R^2	0.019	0.017	0.241	0.230

NOTE: The main dependent variable is Δy_t, the log-difference of real GDP per capita from year $t-1$ to year t. Explanatory variables: $\Delta\hat{s}_t$ = 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. Specifications in Panel A also include Δy_{t-1} and dummy variables for WWII (1942–45) and the Korean War (1950–53), while those in the Panel B include Δy_{t-1} (not reported). The explanatory variables in the auxiliary forecasting equation for Δs_t (columns 3–4) are $\log \mathrm{HYS}_{t-2}$, 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 *** $p < .01$.

the banking system than via the bond market. Thus, 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 a couple of regressions over the full (1929–2013) sample period that echo those of Schularick and Taylor (2012) and Jordà, Schularick, and Taylor (2013). 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 bank credit over the 5-year period ending in year $t-1$ ($\Delta_5 \log \mathrm{BC}_{t-1}$). 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 just bank loans ($\Delta_5 \log \mathrm{BL}_{t-1}$), rather than total bank credit. In both cases, we obtain statistically significant negative coefficients, confirming that there does indeed appear to be a dark side to bank credit booms.

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 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 -4.23 reported in column (1) of Table 5, while that on bank loan growth is of the wrong sign and completely insignificant. In column (3), bank credit growth fares a bit better, retaining marginal statistical significance, but the coefficient on $\Delta\hat{s}_t$ remains strongly significant and is only modestly reduced.

The lower panel of Table 8 is identical to the upper panel, except that it focuses on the 1952–2013 sample period. Here the contrast 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. We would not want to argue that the story that we have in mind is fundamentally different from that of Schularick and Taylor (2012) and Jordà, Schularick, and Taylor (2013), and that we have somehow managed to separate them in the data. The two stories clearly overlap. For example, it is hard to imagine that bank loan supply could expand rapidly without putting downward pressure on spreads in the corporate bond market, as there must be some degree of arbitrage across the two markets. So perhaps we have just found an alternative measurement technique that does a more robust job of capturing variation in credit-market sentiment, particularly outside of the most extreme episodes in our sample period, such as the Great Depression.

At the same time, while the two stories have much in common, they do differ in their emphasis, and these differences have potentially interesting policy implications. Implicit in the approach of Schularick and Taylor (2012) and Jordà, Schularick, and Taylor (2013) is the premise that the banking system is at the center of credit intermediation, and that it is damage to banks that leads to adverse economic outcomes. This logic implies that a policy focus on safeguarding the banking system—via higher capital requirements, for example—might be all that is needed to improve macroeconomic stability. By contrast, our results suggest that disturbances in credit supply that originate outside of the banking sector—in particular, in the corporate bond market—can also have significant consequences for economic activity. If this is the case, then a policy focus that is entirely bank-regulation-centric may be incomplete, a point also made recently by Feroli, Kashyap, Schoenholtz, and Shin (2014).

2.9 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 effect on real activity. In other words, to the extent that indicators of market overheating—unusually low credit spreads and high levels 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

Table 9: Asymmetric Effects of Changes in Credit-Market Conditions on Economic Growth

	Dependent Variable: Δy_{t+1}			
	1929–2013	1952–2013	1973–2013	
Regressors	(1)	(2)	(3)	(4)
$\Delta s_t^{(+)}$	-2.460^{**}	-1.762^{***}	-1.511^{***}	.
	(1.051)	(0.380)	(0.280)	
$\Delta s_t^{(-)}$	-1.405^{***}	-0.794	-0.810^{*}	.
	(0.449)	(0.653)	(0.475)	
$\Delta\text{EBP}_t^{(+)}$	.	.	.	-2.327^{***}
				(0.591)
$\Delta\text{EBP}_t^{(-)}$	.	.	.	-0.541^{**}
				(0.265)
R^2	0.505	0.303	0.385	0.466
$\Pr > W^{a}$	0.255	0.209	0.178	0.013

NOTE: The dependent variable is Δy_{t+1}, the log-difference of real GDP per capita from year t to year $t+1$. The entries denote the OLS estimates of the coefficients associated with $\Delta s_t^{(+)}$ and $\Delta s_t^{(-)}$, the positive and negative changes in the Baa-Treasury spread, respectively, and $\Delta\text{EBP}_t^{(+)}$ and $\Delta\text{EBP}_t^{(-)}$, the positive and negative changes in the excess bond premium (Gilchrist and Zakrajšek, 2012), respectively. Additional explanatory variables (not reported) include a constant, Δy_t, and for the sample period 1929–2013, dummy variables for WWII (1942–45) and the Korean War (1950–53). 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] p-value of the Wald test of the null hypothesis that the coefficients on $\Delta s_t^{(+)}$ and $\Delta s_t^{(-)}$ or $\Delta\text{EBP}_t^{(+)}$ and $\Delta\text{EBP}_t^{(-)}$ are equal.

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.[15]

Nevertheless, it is of obvious interest to see whether the data are suggestive of any asymmetries. Table 9 takes a first cut at the question. In column (1) of the table, we revisit our simple OLS regression from column (1) of Table 1, where changes in credit spreads in year t are used to forecast changes in real GDP in year $t+1$ over the full (1929–2013) sample period; the one modification is that we now allow for different coefficients on credit-spread increases ($\Delta s_t^{(+)}$) and decreases ($\Delta s_t^{(-)}$). As can be seen, at about -2.5, the estimate of the coefficient on credit-spread increases is moderately larger in absolute terms than the estimate of -1.4 of the coefficient on credit-spread

[15] Bordalo, Gennaioli, and Shleifer (2015) develop a behavioral model of the credit cycle that has this symmetry property.

Table 10: Asymmetric Effects of Credit-Market Sentiment on Economic Growth

	Dependent Variable: Δy_t		
Regressors	1929–2013	1952–2013	1973–2013
$\Delta\hat{s}_t^{(+)}$	0.156	−2.413	−3.260*
	(2.972)	(3.869)	(4.250)
$\Delta\hat{s}_t^{(-)}$	−6.871**	−3.335*	−2.920**
	(2.530)	(2.155)	(1.760)
R^2	0.398	0.170	0.408
Difference[a]	7.027	0.922	−0.340
	(4.781)	(4.819)	(4.898)

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, Δy_{t-1}, and for the sample period 1929–2013, dummy variables for WWII (1942–45) and the Korean War (1950–53). The explanatory variables in the auxiliary forecasting equation for Δs_t are $\log \text{HYS}_{t-2}$, 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 $\Delta\hat{s}_t^{(-)}$.

decreases. This loosely suggests that contractions in the supply of credit are associated with stronger effects on future economic growth than increases in supply. However, the difference between these two effects is not statistically significant. Columns (2) and (3) display qualitatively similar results for the sample periods 1952–2013 and 1973–2013, 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 the 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 larger than the effect of an easing.[16]

In Table 10, 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 (1929–2013) sample period. Here the point estimates yield a striking asymmetry: the effect of negative values of $\Delta\hat{s}_t$ is very large in absolute magnitude, while the effect of positive values is near zero. This would seem to suggest that everything is 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.

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

Columns (2) and (3) replicate the specification of column (1) for the shorter and better-behaved sample periods 1952–2013 and 1973–2013, 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 1929–2013 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 is less noisy, there does not seem to be decisive evidence of an asymmetry in one direction or the other.

3 Exploring the Mechanism

In the previous section, we demonstrated that heightened levels of credit-market sentiment are bad news for future economic activity. As we have outlined, 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. In this section we attempt to further flesh out this credit-supply hypothesis. We begin with a simple model that illustrates how data on firms' financing choices can help untangle credit demand and credit supply effects. We then undertake a series of tests motivated by the model. In particular, we show that our proxy for credit-market sentiment not only predicts changes in real activity, but also forecasts changes in the aggregate debt-equity mix for nonfinancial firms. We also show that, consistent with the model, credit-market sentiment has more predictive power for the investment decisions of firms with lower credit ratings.

3.1 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 (2014). 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:

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

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:

$$\theta f(I) - \delta dI - I\frac{\gamma}{2}\big(d - d^*\big)^2. \tag{6}$$

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

$$\theta f'(I) = \delta d + \frac{\gamma}{2}\big(d - d^*\big)^2; \tag{7}$$

$$d = d^* - \frac{\delta}{\gamma}. \tag{8}$$

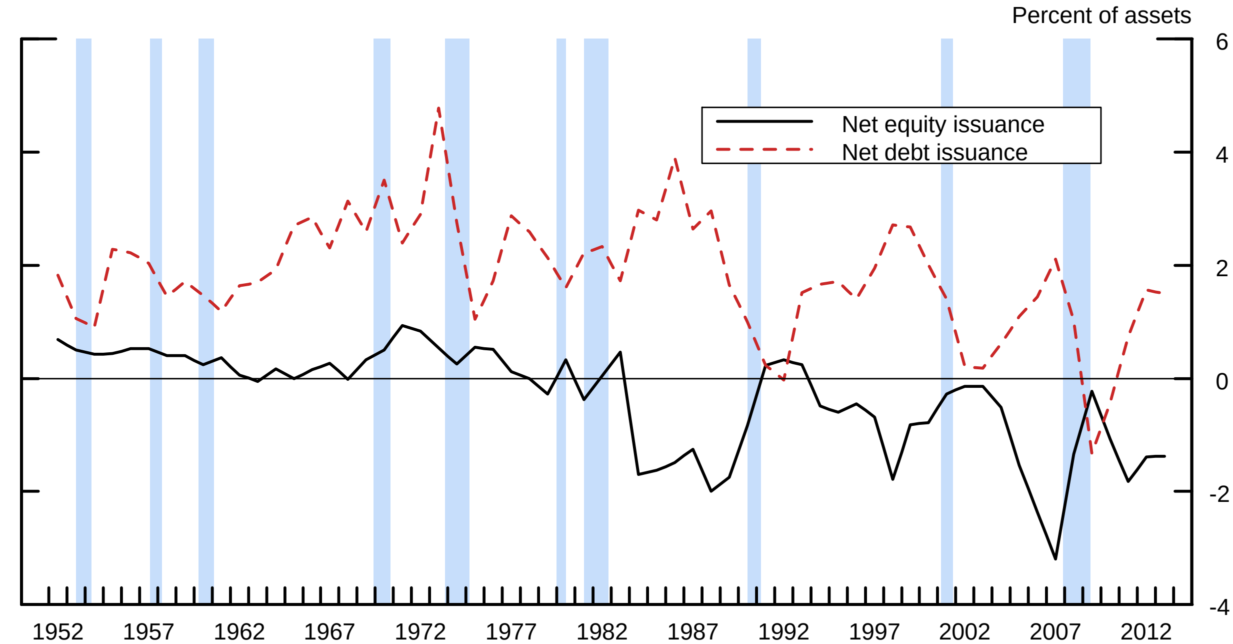
Substituting equation (8) into equation (7) gives

$$\theta f'(I) = \delta d^* - \frac{\delta^2}{2\gamma}. \tag{9}$$

Equations (8) and (9) 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 our results from the previous section. 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 (9) that these two hypotheses cannot be separated. However, equation (8) 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 observation 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-

Figure 6: Corporate Financing Mix

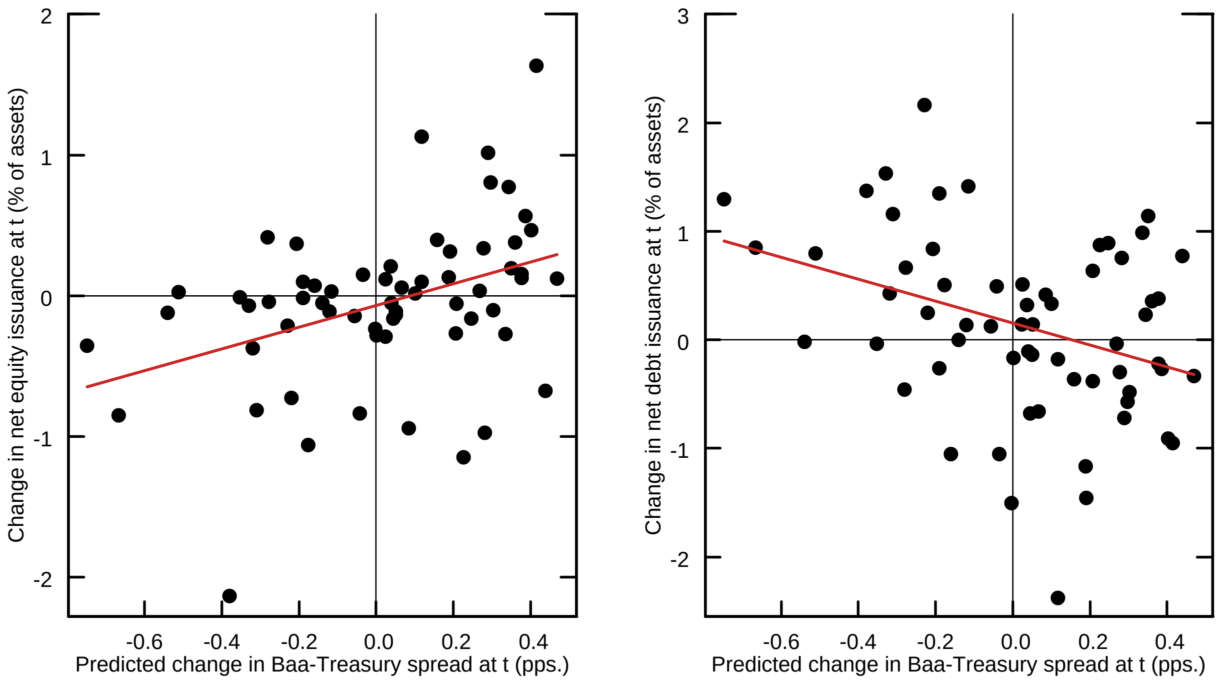


NOTE: The solid line depicts net equity issuance in the U.S. nonfinancial corporate sector, while the dotted line depicts net (long-term) debt issuance; both series are expressed as a percent of the beginning-of-period book-value of total assets. The shaded vertical bars denote the NBER-dated recessions.

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 (9).

We test these predictions below. 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 size of the macroeconomic effects documented in Section 2. 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—that is, higher spreads on asset-backed securities also make it more expensive for households to obtain automobile and other consumer loans. 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.

Figure 7: Changes in Corporate Financing Mix and Credit-Market Sentiment



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.

3.2 Evidence from the Corporate Financing Mix

Our first set of tests uses the Federal Reserve's Flow-of-Funds data from 1952 to 2013 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 6. As pointed out by Ma (2014), there is a striking negative correlation between the two 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 latter.[17]

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 7 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

[17] Ma (2014) 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: Credit-Market Sentiment and Changes in Corporate Financing Mix (Aggregate Flow of Funds Data)

	Dependent Variables	
Regressors	ΔNEI	ΔNDI
A. *Sample Period:* 1952–2013		
$\Delta\hat{s}_t$	1.018***	−1.039**
	(0.322)	(0.428)
r_t^M	0.001	.
	(0.003)	
$\Delta i_t^{(10y)}$	.	−0.234***
		(0.042)
Δy_t	−0.058*	0.151***
	(0.035)	(0.022)
R^2	0.237	0.490
Effect on ΔFMIX[a]	2.057***	
B. *Sample Period:* 1985–2013		
$\Delta\hat{s}_t$	0.720**	−0.728**
	(0.324)	(0.341)
r_t^M	0.000	.
	(0.003)	
$\Delta i_t^{(10y)}$	.	−0.205***
		(0.077)
Δy_t	−0.173***	0.223***
	(0.018)	(0.019)
R^2	0.472	0.504
Effect on ΔFMIX[a]	1.447**	

NOTE: The main 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. Explanatory variables: $\Delta\hat{s}_t$ = 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 (1982–2013). 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 $\log \text{HYS}_{t-2}$, 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.

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 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 business sector output Δy_t; the 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 predicts 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 2013, as well as the more recent period since the mid-1980s. Moreover, the coefficient estimates for equity issues and debt issues are very similar in magnitude, suggesting that based on our sentiment proxy, we are able to predict two years ahead of time what is effectively a dollar-for-dollar shift in the corporate financing mix. This pattern is just what is envisioned by our simple model.

It is worth being clear on the distinction between our results and those of Ma (2014). 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 Flow-of-Funds 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 2013, we create a panel of all nonfinancial firms with a senior unsecured credit rating. We then regress both their change in net equity issuance for year t, as well as their change in net long-term debt issuance, on $\Delta\hat{s}_t$, controlling for firm fixed effects. In variants of these specifications, we also add controls for 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 Table 12 shows, the results from this firm-level analysis are very similar to those from the aggregate Flow-of-Funds 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, again suggesting a roughly dollar-for-dollar substitution of equity for debt when buoyant credit-market sentiment unwinds. Thus it appears that our sentiment indicator is indeed

Table 12: Credit-Market Sentiment and Changes in Corporate Financing Mix
(Firm-Level Compustat Data)

	Dependent Variables			
Regressors	ΔNEI	ΔNDI	ΔNEI	ΔNDI
$\Delta\hat{s}_t$	0.955**	−1.233***	1.224***	−0.973**
	(0.475)	(0.441)	(0.436)	(0.389)
$\Delta \log Y_{jt}$	.	.	−0.005	0.051***
			(0.007)	(0.006)
r_{jt}	.	.	0.011***	0.002
			(0.002)	(0.004)
R^2 (within)	0.002	0.001	0.006	0.007
Effect on ΔFMIX[a]	2.188***		2.217***	

NOTE: Sample period: annual data from 1985 to 2013. Panel dimensions: No. of rated firms = 1,778; $\bar{T}_j = 8.3$ (years); and Total obs. = 14,770. The dependent variables are $\Delta\mathrm{NEI}_{jt}/A_{j,t-1}$ and $\Delta\mathrm{NDI}_{jt}/A_{j,t-1}$, 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. Explanatory variables: $\Delta\hat{s}_t$ = predicted change in the Baa-Treasury spread; $\Delta \log Y_{jt}$ = 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 $\log \mathrm{HYS}_{t-2}$, 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] 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 ($\Delta\mathrm{NEI}/A$) and the change in net debt issuance ($\Delta\mathrm{NDI}/A$), scaled by the beginning-of-period total assets.

able to forecast a true firm-level change in the financing mix and is not simply picking up some sort of compositional effect.

3.3 Investment Behavior of Firms By Rating Category

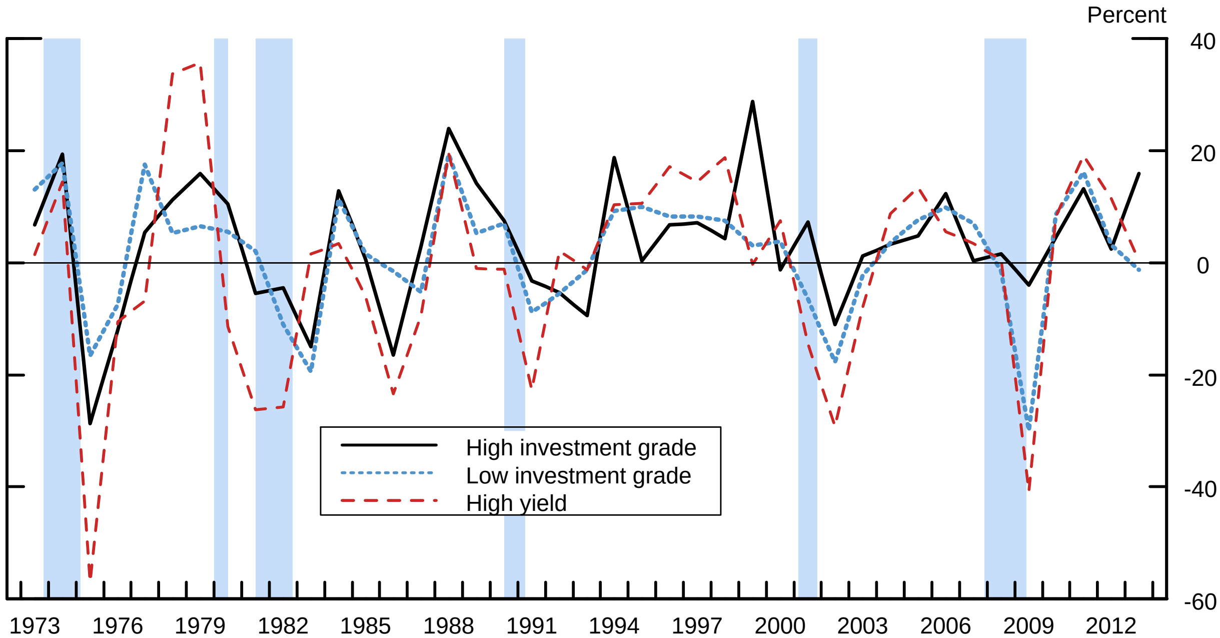
Finally, we turn to a comparison of the investment behavior of firms in different credit-rating categories. To do so, we use Compustat data on nonfinancial firms with senior unsecured credit ratings from 1973 to 2013 to run the following panel regression:

$$\Delta \log I_{jt} = \beta_k \Delta\hat{s}_t \times \mathbf{1}[\mathrm{RTG}_{j,t-1} = k] + \gamma_1 \Delta \log Y_{jt} + \gamma_2 r_{jt} + \eta_j + \epsilon_{jt}. \tag{10}$$

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 change in the firm's real sales $\Delta \log Y_{jt}$; its stock return r_{jt}; 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).[18] Thus with this specification, we are asking whether elevated

[18] 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.

Figure 8: Growth of Capital Expenditures by Type of Firm



Note: The solid line depicts the growth rate of aggregate 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 growth rate of aggregate 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 growth rate of aggregate 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.

credit-market sentiment at time $t-2$ forecasts a more negative outcome for the time-t investment of firms with low credit ratings than for the time-t investment of firms with high credit ratings.

The potential importance of the firm-level covariates can be seen in Figure 8, 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 of the lower-rated firms is considerably more procyclical than the investment 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

Table 13: Credit-Market Sentiment and Investment by Type of Firm
(Firm-Level Compustat Data)

Regressors	Dependent Variable: $\Delta \log I_{jt}$ (1)	(2)
$\Delta\hat{s}_t \times \mathbf{1}[\text{RTG}_{j,t-1} = \text{HY}]$	-14.410^{***}	-10.709^{***}
	(3.861)	(3.377)
$\Delta\hat{s}_t \times \mathbf{1}[\text{RTG}_{j,t-1} = \text{Low IG}]$	-10.473^{***}	-5.396^{**}
	(2.808)	(2.2422)
$\Delta\hat{s}_t \times \mathbf{1}[\text{RTG}_{j,t-1} = \text{High IG}]$	-5.046^{*}	-0.642
	(2.699)	(2.195)
$\Delta \log Y_{jt}$	.	0.919^{***}
		(0.042)
r_{jt}	.	0.014
		(0.022)
R^2 (within)	0.008	0.120
$\Pr > W_{HY=HIG}$[a]	0.001	0.007
$\Pr > W_{LIG=HIG}$[b]	0.029	0.041

NOTE: Sample period: annual data from 1973 to 2013. Panel dimensions: No. of rated firms = 1,786; $\bar{T}_j = 9.7$ (years); and Total obs. = 17,391. The dependent variable is $\Delta \log I_{jt}$, the log-difference of real capital expenditures of firm j from year $t-1$ to year t. Explanatory variables: $\Delta\hat{s}_t$ = predicted change in the Baa-Treasury spread; $\Delta \log Y_{jt}$ = log-difference of real sales of firm j; and r_{jt} = total (log) return of firm j. $\Delta\hat{s}_t$ is interacted with $\mathbf{1}[\text{RTG}_{j,t-1}]$, 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 $\log \text{HYS}_{t-2}$, 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] 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.

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 time $t-2$ credit-market sentiment is associated with a decline in the growth of capital expenditures for a typical firm of about 14 percentage points over the course of year t. By contrast, for low-investment grade firms the corresponding estimate is 10 percentage points, and for high investment-grade firms it is only 5 percentage points.

The second column of the table adds the firm-level controls. Not surprisingly, doing so 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 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 about 11 percentage points for a high-yield firm, 5 percentage points for a low investment-grade firm, and less than one percentage point for a high investment-grade firm. This 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.

4 Possible Implications for Monetary Policy

Although time-varying credit-market sentiment—or equivalently, a time-varying credit-risk premium—plays a central role in our narrative, we have been silent on its source of variation, in effect treating it as exogenous. But what drives this variation in sentiment? One can imagine a number of potential factors. Mistaken beliefs on the part of investors are one possibility. For example, after a few years of economic expansion, with relatively few defaults, overly-extrapolative investors might begin to pay too little attention to default risk, leading to compressed credit spreads (Gennaioli, Shleifer, and Vishny, 2012; Bordalo, Gennaioli, and Shleifer, 2015). However, Stein (2013) argues that while mistaken beliefs may be important, they are unlikely to be the whole story behind time-varying expected returns in credit markets, especially given the centrality of financial intermediaries in these markets. Various contracting frictions and agency problems at the intermediary level are also likely to be an important part of the mechanism.

One strand of recent literature highlights the importance of intermediaries' balance sheets. For example, Adrian, Etula, and Muir (2014) argue that in a world of segmented markets and financing frictions, the wealth of broker-dealers is effectively the stochastic discount factor that prices risky assets in the economy—so that 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) develop a dynamic asset pricing model with an intermediary sector that has similar implications. They also stress that their model is particularly likely to apply to the pricing of various types of credit risk, as opposed to pinning down the equity market premium.[19] Another complementary line of work focuses on an agency problem between intermediaries and their shareholders and argues that this agency problem is intensified when the general level of interest rates is low because it makes intermediaries more likely to "reach for yield"–that is, to accept lower premiums for bearing duration and credit risk—at such times.[20]

Although we have not provided any evidence to help parse these different effects, we believe that our results may have particularly interesting policy implications if one accepts the key premise of the reach-for-yield literature, namely that accommodative monetary policy is one of the factors that can lead to a compression of credit-risk premiums. To see this point, suppose that the central

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

[20]See, for example, Rajan (2006); Borio and Zhu (2008); Jiménez, Ongena, Peydró, and Saurina (2014); Hanson and Stein (2015); and Gertler and Karadi (2015).

bank has the following simple objective function:

$$\min E_t \left[\sum_{j=t}^{\infty} \beta^{j-t} \big(U_j - U^* \big)^2 \right],$$

where U_j is the unemployment rate at time j, U^* is the policymaker's target level for the unemployment rate, and β is a discount factor. Thus the central bank seeks to minimize the expected discounted sum of squared deviations of the unemployment rate from its target. Suppose further that the unemployment rate today is above its target level, and the central bank is providing aggressive monetary accommodation in an effort to return it to target. If there is a reach-for-yield effect at work, this will tend to drive credit-risk premiums lower, which, all else equal, should help with the goal of reducing unemployment today.

The question our research raises is whether there is a future price to be paid for today's highly accommodative policy. Specifically, if a policy-induced compression of credit-risk premiums tends to reverse itself in the same way that unconditional movements in credit-risk premiums do, then our results might lead one to believe that easy policy today would be associated with an increase in the unemployment rate somewhere between two and three years down the road. If so, the central bank would face a nontrivial intertemporal tradeoff, even in the absence of any tension between its unemployment and inflation goals: an aggressively accommodative policy would move it closer to its unemployment target today, but might, at the same time, risk pushing unemployment rates in the future further away from the target value.

How should the central bank seek to handle this tradeoff? Clearly, it depends on how far unemployment is from target today. With a quadratic loss function, the marginal benefit of reducing unemployment at any point in time is linearly increasing in the distance from target. So if the unemployment rate today is very high, this marginal benefit is likely to loom large in relation to any future marginal costs, which are evaluated around a presumably lower expected level of unemployment. In contrast, if unemployment today is only slightly above target, the marginal benefit of accommodation could be less than the expected marginal cost of increased unemployment in the future. Thus, even without taking the threat of inflation into consideration, there may be a reason for the central bank to begin gradually removing accommodation as unemployment approaches its target level, especially if credit-market sentiment appears to be elevated.[21]

To be clear, this discussion is intended to be speculative. And even if one agrees with the qualitative arguments, our results are not sufficient to allow for the monetary-policy tradeoff we have outlined to be quantified in such a way as to make it operational. To get anywhere close to this point will require a good deal of further work, both conceptual and empirical.[22] Nevertheless, we do want to highlight what we see as a potentially useful direction for future research.

[21] See Stein (2014) for a similar argument.

[22] For a recent attempt in this direction see Ajello, Laubach, López-Salido, and Nakata (2015).

5 Conclusion

This paper emphasizes the role of credit-market sentiment as an important driver of the business cycle. In so doing, it echoes an older narrative put forward by Minsky (1977) and Kindleberger (1978), which has received renewed attention in light of the recent financial crisis. 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 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 few important 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. We have taken these fluctuations to be exogenous in our empirical work, but one's view regarding their root source clearly matters for how one thinks about policy implications. For example, our results may have something to say about the conduct of monetary policy, particularly in a world in which reach-for-yield effects are prominent. However, fleshing out these implications to the point where one can give useful quantitative advice to policymakers will require a substantial amount of further research.

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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. GFD refers to Global Financial Data database and CRSP refers to the Center for Research in Security Prices.

A.1 U.S. Economic and Financial Data

Real GDP: The data 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 1948–2013 period, we converted the quarterly real GDP to an annual frequency by averaging the series over the four quarters of each calendar year.

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 from the U.S. Census Bureau Historical Data Release. From 1952 onward, the same series is available quarterly from FRED. We converted the quarterly population series to an annual frequency by averaging the series over the four quarters of each calendar year.

Real Business Fixed Investment: The data are from FRED and are in billions of 2009 dollars. For the period 1929–47, the data are available only at an annual frequency; from 1947 onward, they are available quarterly at a seasonally adjusted annual rate. For the 1948–2013 period, we converted the quarterly real business fixed investment 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.

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).

Yield on Baa-Rated Corporate Bonds: The data are from FRED and are available at a month-end 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: The data are from GFD and are available at month-end 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 GFD and are available at various frequencies (daily, weekly, and monthly) since January 31, 1920. We first converted the series to monthly frequency by taking the month-end 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 then 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 2013.

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 2013.

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 Corporate Leverage and Bank Balance Sheets

Aggregate Leverage: The data on aggregate leverage for the U.S. nonfinancial corporate sector (excluding the publicly regulated utilities) are from Graham, Leary, and Roberts (2014). Using a mixture of hand-collected data and firm-level data from Compustat, they constructed several annual measures of corporate leverage going back to the early 1900s. As discussed in the main text, we consider three different measures of leverage:

(1) $[\text{LTD/A}]_t$ = book-value of long-term debt to book-value of total assets

(2) $[\text{TD/A}]_t$ = book-value of total debt to book-value of total assets

(3) $[\text{TL/A}]_t$ = book-value of total liabilities to book-value of total assets

Cross-Sectional Distribution of Leverage: To compute corporate leverage at various points of the cross-sectional distribution, we use firm-level annual data from Compustat, which are available starting in 1950. We focus on the ratio of the book-value of long-term debt to the book-value of total assets ($[\text{LTD/A}]_{jt}$). The book-value of long-term debt (Compustat annual data item #9) is defined as debt obligations due in more than one year from the company's balance sheet date or due after the current operating cycle. The book-value of total assets (Compustat annual data item #6) represents current assets plus net property, plant, and equipment plus other noncurrent assets (including intangible assets, deferred charges, and investments and advances.) As Graham, Leary, and Roberts (2014), we restrict our sample to nonfinancial firms, excluding the publicly regulated utilities. For each year t, we then compute the weighted 50$^{\text{th}}$, 75$^{\text{th}}$, and 90$^{\text{th}}$

percentiles of the distribution of the ratio of long-term debt to assets for a set of firms that are in our sample in both year $t-1$ and year t, using the nominal value of sales in year $t-1$ as weights.

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.

A.3 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.
- 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 ($\Delta \log I_{jt}$), the growth of real sales ($\Delta \log Y_{jt}$), or equity return (r_{jt}), was below the 2.5^{th} or above the 97.5^{th} 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*: 1985–2013[a]				
$\Delta\text{NEI}_{jt}/A_{j,t-1}$	−0.15	6.39	−40.72	54.14
$\Delta\text{NDI}_{jt}/A_{j,t-1}$	0.76	11.34	−31.77	44.74
B. *Sample period*: 1973–2013[b]				
$\Delta \log I_{jt}$				
HY firms	3.58	52.88	−184.84	171.01
Low IG firms	2.76	35.65	−183.27	171.56
High IG firms	4.25	27.95	−147.08	154.26
All firms	3.27	44.37	−184.84	171.56
$\Delta \log Y_{jt}$				
HY firms	6.13	19.90	−63.41	83.23
Low IG firms	4.07	14.56	−63.40	82.08
High IG firms	4.47	11.60	−55.31	72.68
All firms	5.09	17.20	−63.41	83.23
r_{jt}				
HY firms	1.87	46.71	−138.63	109.16
Low IG firms	8.65	31.24	−137.73	109.05
High IG firms	10.35	24.35	−109.43	95.13
All firms	5.51	39.24	−138.83	109.16

NOTE: All variables are expressed in percent; statistics are based on trimmed (P2.5/P97.5) data (see the text for details).

[a] No. of firms = 1,778; Total Obs. = 14,765.

[b] No. of HY firms = 1,397; No. of Low IG firms = 706; No. of High IG firms = 117; No. of firms = 1,786; Total Obs. = 17,391. 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.