The Real Consequences of Market Segmentation*

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November 15, 2011

*We are especially grateful to our advisers Fritz Foley, Robin Greenwood, David Scharfstein, and Jeremy Stein for their guidance and very helpful discussions. We thank Malcolm Baker, Bo Becker, Effi Benmelech, Dan Bergstresser, Alexander Butler, John Campbell, Lauren Cohen, Andrew Ellul, Sam Hanson, Victoria Ivashina, Andrew Karolyi, Darren Kisgen, Erik Stafford, Laura Starks (the editor), an anonymous referee, and seminar participants at Arizona State University, the Bank of Canada, Cornell, the Federal Reserve Bank of Boston, the Federal Reserve Bank of New York, Harvard, the Finance Down Under Conference, Imperial College London, the London School of Economics, the NBER Credit Rating Agencies session, Ohio State University, Rice, the Trans-Atlantic Doctoral Conference, the University of Illinois at Urbana-Champaign, the WFA 2010 Annual Meetings, and Yale for helpful comments and suggestions, Doug Richardson at the Investment Company Institute for providing mutual fund flows data, and Jerome Fons, Martin Fridson, Oleg Melentyev, and Michael Weilheimer for discussing the high-yield market with us. Send correspondence to Sergey Chernenko, Fisher College of Business, The Ohio State University, 818 Fisher Hall, 2100 Neil Avenue, Columbus, OH 43210; telephone: (614) 292-4412; fax: (614) 292-4412. E-mail: chernenko_1@fisher.osu.edu

Abstract

We study the real effects of market segmentation due to credit ratings using a matched sample of firms just above and just below the investment-grade cutoff. These firms have similar observables, including average investment rates. However, flows into high-yield mutual funds have an economically significant effect on the issuance and investment of the speculative-grade firms relative to their matches, especially for firms likely to be financially constrained. The effect is associated with the discrete change in label from investment-grade to speculative-grade, not with changes in continuous measures of credit quality. We do not find similar effects at other rating boundaries. (*JEL* G24, G31)

Capital markets play a critical role in efficiently allocating capital across firms. Their ability to play this role, however, may be impeded by market segmentation. In this paper, we study one of the most prominent divides in capital markets—the distinction drawn between investment- and speculative-grade firms. A large number of regulations, investment charters, and contracts reference this distinction, and recent research suggests that it can affect firms' capital structure and cost of capital (Kisgen, 2006; Kisgen and Strahan, 2010; Ellul, Jotikasthira, and Lundblad, 2011).

Market segmentation between investment- and speculative-grade firms may also have real effects. When investors withdraw capital from high-yield mutual funds, which are large buyers of speculative-grade bonds, arbitrage capital may not immediately offset this shock (Mitchell, Pedersen, and Pulvino, 2007; Duffie and Strulovici, 2011). As a result, such high-yield fund flows may affect the supply and cost of capital available to speculative-grade firms. This in turn may cause some firms, particularly those unable to access other sources of financing, to cut their investment. This paper presents evidence of this mechanism at work.

Simple comparisons between investment- and speculative-grade firms would be confounded by differences in fundamentals between them. Instead, drawing on the econometric literature on treatment effects, we construct a matched sample of firms just above (BBB-) and just below (BB+) the investment-grade cutoff. These firms are similar on observable characteristics and have the same average rates of investment, but flows into high-yield mutual funds only affect the supply and cost of capital for the speculative-grade (BB+) firms. As a consequence, high-yield mutual fund flows, which are largely driven by retail investors, result in the bond issuance and the investment of firms just below the cutoff diverging from the investment of their matches just above the cutoff. This effect is economically meaningful—a one standard deviation increase in high-yield fund flows increases the investment of BB+ firms relative to their BBB- matches by about 10% of their average rate of investment. The effect is stronger for firms that depend on external financing, are more likely to be financially constrained, and have limited ability to substitute to either bank loans or the asset-backed securities market. Our results indicate that market segmentation causes temporary differences in the investment of similar firms, but that these differences tend to average out over time.

Our matching methodology is designed to rule out alternative explanations based on firm investment opportunities. We match BB+ firms to BBB- firms based on industry and firm characteristics including size, leverage, Altman's z-score, Q, cash holdings, asset tangibility, profitability, and sales growth. Our identifying assumption is that firms close to the cutoff with similar observable characteristics are also subject to similar shocks to profitability and investment opportunities. If this is the case, then by differencing the investment rates of matched BB+ and BBB- firms we difference out any common shocks to investment opportunities that may be correlated with high-yield mutual fund flows. We can then interpret the differential effect of high-yield mutual fund flows on the investment of BB+ firms as evidence of recurring capital supply effects.

Despite our matching methodology, one may still worry that the investment opportunities of matched firms may not be exactly the same and that high-yield mutual fund flows may be responding to the differential investment opportunities of less creditworthy firms. This would be the case if, for instance, ratings were driven by unobservable characteristics known to rating agencies. Although we cannot completely rule out differences in unobservable characteristics, we address such concerns in two ways. First, we show that our results are robust to controlling for a variety of macroeconomic variables and are thus unlikely to be driven by differential sensitivities to the business cycle. Second, we conduct falsification tests at other rating boundaries: the investment-grade cutoff is the only one where the investment of firms below the cutoff is more sensitive to high-yield mutual fund flows than the investment of firms above the cutoff.

In summary, we find that shocks to the supply of capital of high-yield mutual funds result in the investment of firms just below the investment-grade cutoff diverging from the investment of similar firms just above the cutoff. Our work is related to the literature studying the investment effects of shocks to the supply of bank capital[1] as well as the literature studying the role of credit ratings in capital markets, with Lemmon and Roberts (2010) being perhaps the most closely related paper. Lemmon and Roberts (2010), one of several papers to study the period surrounding the savings and loan crisis,[2] argue that the collapse of the junk bond dealer Drexel Burnham Lambert constituted a capital supply shock that led speculative-grade firms to cut their acquisitions relative to unrated firms that were previously able to issue debt in private debt markets.

Our work makes three novel contributions to the literature. First, we study how *recurring* shocks to the capital of an important, largely retail-based investor class interact with market segmentation to affect real investment, while the existing literature mostly focuses on the effects of large unexpected one-time changes in the institutional environment.[3] Our results suggest that distortions in real investment due to market segmentation are commonplace, not just isolated events that occur when the institutional environment undergoes dramatic changes. Second, our results emphasize how the investment effects of market segmentation vary with financial market conditions. The existing literature focuses on institutional changes, showing that changes altering the set of creditors firms can access are associated with changes in firm financing behavior. In contrast, our work shows that market segmentation has a particularly important impact on firm investment decisions when flows into high-yield mutual funds deviate from their long-run mean. Our empirical methodology, which adds to a growing literature using matching methods in finance (for example, Villalonga, 2004; Malmendier and Tate, 2009; Almeida, Campello, Laranjeira, and Weisbenner, forthcoming; Campello, Graham, and Harvey, 2010), is important for making this point. While previous work has dealt with the simultaneity of capital supply and demand by seeking out plausibly exogenous supply shocks, our approach seeks to effectively hold demand fixed observation-by-observation. Since market conditions are not exogenous, our methodology is necessary in order to isolate the time-varying effects of market segmentation on firm investment. Finally, by studying the effects of rating-based market segmentation on the financing and investment behavior of firms, we contribute to the current debate on the regulatory role of credit ratings in capital markets.

The remainder of the paper is organized as follows. In the next section we review the institutional background that motivates our empirical methodology, which we discuss in more detail in Section II. Section III describes our data and summarizes differences in firm characteristics across credit ratings. Section IV reports our main results, and Section V concludes.

I Institutional background

We begin by briefly describing two institutional features of credit markets and credit ratings that motivate our empirical methodology. First, many regulations, as well as voluntary conventions, restrict the ability of certain investor classes to hold speculative-grade securities. Second, rating methodologies introduce noise and inertia in credit ratings. Once we review this institutional background, we go on to describe our empirical methodology.

A Regulations restrict holdings of speculative-grade securities

Many rules and regulations restrict the ability of certain investor classes to hold speculative-grade securities. Commercial banks have been prohibited from holding bonds rated BB+ and below since 1936. The Financial Institutions Reform, Recovery, and Enforcement Act of 1989 extended the ban on holdings of speculative-grade bonds to thrifts.[4] Most state insurance regulations follow the guidelines established by the National Association of Insurance Commissioners, which set higher risk charges for and a hard cap on holdings of speculative-grade bonds.[5] In addition, the net capital rule for broker-dealers requires larger haircuts for speculative-grade securities (U.S. Securities and Exchange Commission, 2003).[6]

Although not subject to regulatory restrictions, most bond mutual funds specialize in either investment- or speculative-grade bonds. Investment-grade funds typically limit their holdings of speculative-grade bonds to 5-10% of fund assets. For instance, PIMCO Total Return Fund, the largest corporate bond fund, limits its holdings of high-yield bonds rated B or higher to 10% of fund assets. According to Morningstar, as of June 2011, about 6% of PIMCO's bond holdings were in speculative-grade and unrated securities. Vanguard Short-, Intermediate-, and Long-Term Investment-Grade Funds are more restrictive and invest exclusively in securities rated BBB- and above. Some investment-grade funds, such as Fidelity U.S. Bond Index Fund, do not have explicit limits on the credit quality of their portfolio holdings. Instead, they seek "to provide investment results that correspond to the total return of the bonds in the Lehman Brothers U.S. Aggregate Index." Since the index consists exclusively of investment-grade securities, any speculative-grade holdings would expose such funds to significant tracking error and would thus be quite costly. Not surprisingly, as of June 2011, only 0.6% of Fidelity U.S. Bond Index Fund's bond portfolio was invested in speculative-grade and unrated bonds.

Conversely, high-yield mutual funds specify a minimum share of their assets to be invested in speculative-grade securities. Vanguard High-Yield Corporate Fund must invest "at least 80% of its assets in corporate bonds that are rated below Baa by Moody's Investor Service, Inc. (Moody's); have an equivalent rating by any other independent bond-rating agency." As of June 2011, Vanguard High-Yield Corporate Fund held 94% of its bond portfolio in speculative-grade and unrated bonds. The 80% minimum on holdings of speculative-grade bonds is typical—according to Morningstar, as of June 2011 high-yield mutual funds on average had 93% of their bond portfolios invested in speculative-grade and unrated bonds.

Finally, note that any speculative-grade bond purchases by investment-grade funds and investment-grade bond purchases by high-yield mutual funds will introduce noise in our measure of the supply of capital available to speculative-grade firms, and thus bias us against finding any results.

B The muddled origins of "investment grade"

Given the large number of restrictions on investing in speculative-grade securities, one may worry that differences in firm characteristics and investment opportunities may be especially stark at the investment-grade cutoff. We examine differences in observable firm characteristics below, but the origins of the cutoff may also mitigate some of these concerns. When Moody's published the first credit ratings in 1909, it used the term "grade" to refer to three groups of credit ratings: AAA, AA, and A bonds constituted the "first-grade," BBB and BB bonds the "second-grade," B and lower rated bonds "low grade" (Harold, 1938; Fons, 2004).[7] Thus in contrast to the modern distinction between BBB and BB bonds, Moody's originally thought of them as being of similar quality.[8]

It was not until the 1930s that the modern distinction between speculative- and investment-grade bonds began to emerge. In 1931, the Comptroller of the Currency ruled that commercial banks could carry bonds rated BBB or higher at cost, but that they had to mark to market lower rated and defaulted bonds.[9] In 1936, the Comptroller and the Federal Reserve went further and completely prohibited commercial banks from purchasing "'investment securities' in which the investment characteristics are distinctly or predominantly speculative" (Harold, 1938).

The ruling caused significant confusion regarding the precise definition of "speculative" securities. *American Banker* initially concluded that the "regulation limits investments practically to those with an A rating" (Harold, 1938). However, by 1938 Moody's had persuaded the regulators that bonds rated BBB were not "distinctly or predominantly speculative." This history suggests that the investment-grade cutoff was not originally drawn to distinguish between firms with sharply different fundamentals; the cutoff could have just as easily been drawn at A vs. BBB or BB vs. B.

Over time, however, market institutions may have evolved around the cutoff to render its location more correlated with firm characteristics and investment opportunities. Below we provide evidence that this is not the case, showing that differences in observable firm characteristics at the investment-grade cutoff are similar to differences across other rating cutoffs.

C Noise and inertia in credit ratings

Credit ratings do carry information about firms' credit quality and potentially about their investment opportunities.[10] However, if ratings are subject to noise and inertia, we will be able to find pairs of firms that have similar characteristics but are on different sides of the cutoff. There are a number of reasons to believe that credit ratings are noisy, lagging measures of credit quality. First, ratings methodologies emphasize stability. The agencies explicitly trade off rating accuracy versus stability and are reluctant to upgrade or downgrade firms if such changes might have to be reversed in the future (Cantor and Mann, 2006). This is particularly true at the investment-grade cutoff, as the agencies are aware that their decisions affect the ability of market participants to hold certain bonds. Moreover, even when the agencies do adjust credit ratings, the adjustment is likely to only be partial, and followed by additional changes (Altman and Kao, 1992). As a result, market-based measures such as yield spreads are more accurate than credit ratings in forecasting defaults at short- and medium-term horizons (Cantor and Mann, 2006).

In addition to the inertia in ratings generated by the explicit goal of stability, credit rating agencies' organizational structures may create incentives for analysts to be conservative in upgrading or downgrading firms. One such organizational practice, used by Moody's Leveraged Finance Group, is having separate groups analyzing investment- and speculative-grade credits. This organizational structure could create conflicts of interest as the group covering a particular firm would lose fee revenue if it upgraded or downgraded the client across the investment-grade cutoff.

Rating outlooks introduce a further wedge between the information and regulatory content of credit ratings. These outlooks "assess the potential for an issuer rating change" but are not "necessarily a precursor for a rating change" (Standard & Poor's, 2008). On average, however, issuers with a positive outlook default at the same rate as issuers rated one notch higher (Cantor and Hamilton, 2005). Over the 1995-2005 period, BB+ firms with a positive outlook had a 5-year default rate of only 0.95%, significantly lower than the 3.88% default rate of BBB- firms with stable outlook (Cantor and Hamilton, 2005). In fact, when reporting how accurately credit ratings forecast default "Moody's traditionally adjusts an issuer's rating . . . 1 notch downwards (upwards) for negative (positive) outlook" (Moody's, 2011). Thus, although the information content of a BB+ rating with a positive outlook is the same as, if not better than, that of an unconditional BBB- rating, their regulatory implications are quite different—until they are actually upgraded, BB+ firms with positive outlooks cannot access the investment-grade market.

II Empirical methodology

The previous section suggests two stylized facts that drive our empirical approach. First, regulations and investment charters restrict the ability of many investor groups to hold speculative-grade securities. Thus, shocks to the capital of investors who can hold speculative-grade bonds may have a significant effect on the ability of speculative-grade firms to raise capital and invest. In our empirical implementation, we focus on high-yield mutual funds, an investor class which holds about 20% of speculative-grade bonds and experiences recurring capital shocks due to fund flows.

Second, noise and inertia in credit ratings imply there are BB+ firms that are similar to BBB- in terms of firm characteristics and investment opportunities. That is, there are firms rated BB+ that "should be" BBB- and vice versa. Our empirical strategy is to match BB+ and BBB- firms based on industry and firm characteristics, and to compare the investment sensitivities of the matched firms to high-yield mutual fund flows.[11]

Our benchmark matching procedure uses industry, size, leverage, Altman's z-score, Q, cash holdings, and sales growth. These variables have the most explanatory power in regressions of BB+ versus BBB- rating on firm characteristics. Each quarter we take a firm rated BB+ and find a BBB- firm that is in the same Fama-French 48 industry and is the closest in terms of our matching variables. We measure closeness using the Mahalanobis norm, which measures the distance between firm characteristics accounting for the variance of individual characteristics and the covariances between characteristics, as is standard in the literature. Although it would be possible to mechanically find the closest BBB- firm for every BB+ firm, we would like to ensure high-quality matches where the BB+ firm and its BBB- match are very similar. To do so, we require the difference in each matching variable to be less than one standard deviation of that variable.

In addition to our benchmark matched sample, we also separately examine the subset of BB+ firms with positive rating outlooks. These firms have observable characteristics and default rates similar to BBB- firms, but they are still subject to the capital supply shocks associated with high-yield mutual fund flows.

Our approach is similar in spirit to the pseudo-experimental approaches used to estimate treatment effects in the program evaluation literature. Consider a firm i with true (continuous measure of) credit quality S_i and assigned credit rating R_i. Its investment can be written as a function of standard investment regression controls and flows into high-yield mutual funds:

$$\begin{aligned} Inv_{i,t} = {} & \alpha_i + \beta_Q \cdot Q_{i,t-1} + \beta_{CF} \cdot CF_{i,t} \\ & + \beta_{Flows}(R_i) \cdot \textit{High-yield fund flows}_{t-1} + \textit{Investment opportunities}_t(S_i) + \varepsilon_{i,t} \end{aligned} \tag{1}$$

We assume that unobservable common shocks to $\textit{Investment opportunities}_t(S_i)$ vary continuously with the true credit quality S_i, while the sensitivity of investment to high-yield fund flows, $\beta_{Flows}(R_i)$, depends on the assigned rating because of the regulatory frictions described above. In particular, the institutional restrictions discussed above suggest that $\beta_{Flows}(BB+) > 0$ and $\beta_{Flows}(BBB-) = 0$.

Individual firms are too small for aggregate high-yield fund flows to be correlated with the firm-specific shocks $\varepsilon_{i,t}$. Fund flows are potentially correlated with the common shocks $\textit{Investment opportunities}_t$, which would bias the coefficient β_{Flows} upward if we ran the simple regression above. However, if our matching procedure is effective, we can find a BBB- firm j that has very similar underlying credit quality, S_j, and hence is subject to the same common investment opportunities shocks, i.e. $\textit{Investment opportunities}_t(S_i) = \textit{Investment opportunities}_t(S_j)$. We can then difference the two equations to obtain

$$Inv_{i,t} - Inv_{j,t} = (\alpha_i - \alpha_j) + (\beta_{Flows}(BB+) - \beta_{Flows}(BBB-)) \cdot \textit{High-yield fund flows}_{t-1} + \beta_Q \cdot (Q_{i,t-1} - Q_{j,t-1}) + \beta_{CF} \cdot (CF_{i,t} - CF_{j,t}) + (\varepsilon_{i,t} - \varepsilon_{j,t})$$

or more compactly

$$\Delta Inv_{i,t} = \alpha + \beta_{Flows} \cdot \textit{High-yield fund flows}_{t-1} + \beta_Q \cdot \Delta Q_{i,t-1} + \beta_{CF} \cdot \Delta CF_{i,t} + \eta_{i,t} \tag{2}$$

where $\Delta X = X^{BB+} - X^{BBB-}$ is the difference in firm characteristic X between matched BB+ and BBB- firms. By differencing the investment of matched firms, we thus remove any correlation between high-yield fund flows and investment opportunities. Finding a positive and statistically significant coefficient β_{Flows} is then evidence of a capital supply effect of fund flows on the investment of BB+ firms.

A Limitations of the approach

Our empirical methodology is designed to compare pairs of firms that are subject to the same investment opportunities shocks. However, we can only verify that our matched firms are similar on *observable* characteristics. If matched firms differ on unobservable characteristics that are known to the credit rating agencies, then their investment opportunities may not quite be the same.

In the absence of a true experiment we cannot completely rule out this concern. However, we attempt to address it in two ways. First, we show that our results are robust to controlling for a variety of macroeconomic variables and are thus unlikely to be driven by differential sensitivities to the business cycle. Second, we conduct falsification tests comparing the sensitivity of investment to high-yield mutual fund flows around other rating cutoffs—the investment-grade cutoff is the only one where the investment of firms below the cutoff is more sensitive to fund flows than the investment of firms above the cutoff. If our results were driven by unobservable firm characteristics known to the credit rating agencies, then we would expect to find differential investment sensitivities around every cutoff.

Another limitation of our empirical approach is that firms could be selecting into different ratings based on unobservable characteristics. The distribution of credit ratings shown in Figure 1 suggests that some selection might be taking place, as there are fewer firm-quarter observations rated BB+ than either BBB- or BB. Although the direction of any bias introduced by selection on unobservable characteristics is ambiguous, we believe that the most natural selection story would bias us against finding our results. The firms whose investment would be most affected by the volatility of high-yield fund flows if they were rated BB+ have the strongest incentives to alter their behavior to achieve a BBB- rating. Thus, firms that do carry a BB+ rating in our data are likely to have a relatively low sensitivity of investment to high-yield fund flows.

Management of an existing rating could also introduce bias into our results. A firm desiring to protect or increase its rating might cut investment in order to do so. If such behavior occurs at many rating cutoffs and drives our results, then our falsification tests around other rating cutoffs would fail. Of course, rating management could be most important around the investment-grade cutoff. For instance, BBB- firms that are in danger of being downgraded might cut investment in the hopes of maintaining their (valuable) investment-grade status. In contrast, BB+ firms are already speculative grade, so they have less to lose if downgraded and may be less likely to cut their investment to maintain their ratings. Note, however, that for such behavior to drive our results, downgrades would have to be more common when high-yield fund flows are high. In practice, downgrades tend to be countercyclical while high-yield fund flows tend to be procyclical, so such a bias would work against finding our results.

To summarize, while our empirical methodology is designed to rule out alternative interpretations of our results, it has some limitations. Our macroeconomic controls and our falsification tests, as well as our cross-sectional results, help alleviate concerns about unobservable characteristics and rating management but cannot completely eliminate them.

III Data

In this section we describe our sample construction and address three data-related issues before turning to our results. First, we discuss which of a firm's potentially numerous credit ratings determines whether it can access the investment-grade market. Second, we examine differences in firm characteristics across credit ratings to show that there is no abrupt change in firm characteristics around the investment-grade cutoff. Third, we explain how we measure high-yield fund flows, and show that flows are large relative to the capital and investment of speculative-grade firms.

A Sample construction

Our sample covers domestic firms in the quarterly CRSP/Compustat merged data set, excluding financials and utilities, over the 1986Q1-2010Q4 period. The sample period is determined by the availability of S&P domestic long-term issuer credit ratings in Compustat starting in December 1985. Some of our specifications use rating outlooks and bank loan ratings from the S&P RatingsDirect and Ratings IQuery databases.

We measure investment as $\frac{CAPX_{i,t}}{PPE_{i,t-1}}$, the ratio of capital expenditures in quarter t to net property, plant, and equipment at the end of quarter $t-1$.[12] Our regressions include standard controls: cash flow normalized by lagged capital, $\frac{CF_{i,t}}{PPE_{i,t-1}}$, and $Q_{i,t-1}$. We also use size, leverage, Altman's z-score, cash holdings, and sales growth in our matching procedure. A list of variable definitions is in the Appendix in Table 8. To reduce the effect of outliers we winsorize all variables at the first and ninety-ninth percentiles.

B Measuring access to the investment-grade market

While regulations distinguish between investment and speculative grades at the security level, investment activity occurs at the firm level. We therefore need a firm-level measure of access to the investment-grade market. The senior secured credit rating is typically the highest rating a firm can achieve on an individual security and is therefore the right measure of access to the investment-grade market. A firm with a BB+ senior *secured* rating has no way to access the investment-grade market during periods of low or negative flows into high-yield mutual funds.[13] In comparison, a firm with a BB+ senior *unsecured* rating that has unencumbered collateral may still be able to access investment-grade market by issuing senior secured debt.

We use the S&P long-term issuer credit rating, which is a "current opinion of an issuer's overall creditworthiness, apart from its ability to repay individual obligations" and corresponds closely to the senior secured rating (Standard & Poor's, 2008). S&P may "notch up"—rate individual issues above the issuer credit rating—when it "can confidently project recovery prospects exceeding 70%" (Standard & Poor's, 2008). Since few firms are in position to issue senior secured bonds with recovery prospects exceeding 70%, the S&P long-term issuer credit rating is a good measure of the firms' ability to access the investment-grade market.[14] And to the extent that some firms with BB+ senior secured ratings are able to issue higher rated securities, we will be less likely to find any effect of high-yield fund flows on the investment of speculative-grade firms.

C No break in firm characteristics at the investment-grade cutoff

Our identification strategy and falsification tests require that differences in firm characteristics at the investment-grade cutoff be similar to differences across other rating cutoffs. Table 1 reports the means of firm characteristics by credit rating. As there are few AAA and AA+ firms, we combine these firms into one category. We do the same for firms rated CCC+ through CCC-.

Lower-rated firms are generally smaller and more levered. In addition, they have lower values of Altman's z-score than higher-rated firms. The ratio of net property, plant, and equipment to assets is relatively constant across credit ratings. Q varies from 2.5 for the most highly rated firms to 1.4 for CCC rated firms. Higher-rated firms are more profitable than lower-rated firms, whether one looks at operating margins, ROA, or cash flow. Despite significant differences in Q across credit ratings, and with the exception of CCC rated firms that are likely to be in financial distress, firms appear to engage in similar levels of capital expenditures.

Importantly, the investment-grade cutoff does not stand out compared to other rating cutoffs. BB+ firms are on average about 30% smaller than BBB- firms, but there are similar differences in size around other lower rated cutoffs, and our empirical methodology matches on size to produce a sample of comparably sized firms. The market leverage of BB+ firms is 9% higher than the market leverage of BBB- firms, but there are only two other cutoffs with smaller percentage differences in market leverage. BB+ firms have somewhat higher operating margins but lower ROA and cash flow than BBB- firms. The investment rate of both BB+ and BBB- firms is around 21.5%.

D Flows are large relative to the investment of BB firms

The time series of aggregate flows into high-yield corporate bond mutual funds is from the Investment Company Institute, the national association of U.S. investment companies. At the end of 2010, the Investment Company Institute collected information on assets and flows from 8,545 mutual funds with $11.8 trillion in assets under management. In our data, assets under management of high-yield mutual funds start at $6 billion in 1986, grow to $168 billion by May 2007, fall to $104 billion in November 2008, and grow to $219 billion by the end of 2010.

The appropriate measure of flows should capture their magnitude relative to the capital of firms close to the investment-grade cutoff, and also account for the time lag between fund flows and bond issuance on one hand and issuance and investment on the other hand. To accomplish these goals, we calculate cumulative flows over the four quarters $[t-4, t-1]$ and scale flows by the total PPE of firms rated BBB+ through BB-, PPE_{t-1}. Our results are robust to calculating flows over other windows and using alternative scalings, in particular scaling flows by total net assets (TNA) of high-yield mutual funds. Figure 2 shows the time-series of high-yield mutual fund flows relative to PPE and capital expenditures of firms rated BBB+ through BB-. Flows vary significantly over time and are large relative to the investment of these firms. In our regressions, we standardize flows so that the coefficients can be interpreted as the effect on investment of a one standard deviation increase in scaled flows.

IV Results

A Characteristics of matched BB+ and BBB- firms

Table 2 reports the characteristics of matched BB+ and BBB- firms. We match 1,056 out of 4,331 firm-quarter observations rated BB+ to 883 unique firm-quarter observations rated BBB-. We report the mean characteristics for each set of firms and the difference in means.

Our matching procedure successfully picks BB+ and BBB- firms that have similar size and leverage. Although in the full sample, BB+ firms are on average 31.2% smaller than BBB- firms, in the matched sample, the BB+ firms are only 4.5% smaller than their BBB-matches, and the difference is not statistically significant. Furthermore, none of the other differences in characteristics between BB+ firms and matched BBB- firms are statistically or economically signficant. Overall, our matching procedure selects a sample of BB+ and BBB- firms that are very similar along observable dimensions.[15]

In addition to the full sample of BB+ firms, we consider the subsample of BB+ firms with positive outlooks.[16] These firms are larger, have lower leverage and higher profitability than other BB+ firms. They are also more profitable and invest more than their BBB- matches. BB+ firms with positive outlooks also have higher values of Q and cash flow than matched BBB- firms, though these differences are not statistically significant. Overall these results are consistent with BB+ firms with positive outlooks having similar default rates as BBB- firms. Yet for regulatory purposes, these firms are still treated as speculative-grade, and as we will see shortly, their investment is still sensitive to flows into high-yield mutual funds.

B Flows increase the investment of BB+ firms relative to BBB- firms

Table 3 reports the results of our baseline regressions. We regress the difference in the investment rates of matched BB+ and BBB- firms on high-yield mutual fund flows and differences in Q and cash flow

$$\Delta \frac{CAPX_{i,t}}{PPE_{i,t-1}} = \alpha + \beta_{Flows} \cdot \textit{High-yield fund flows}_{t-1} + \beta_Q \cdot \Delta Q_{i,t-1} + \beta_{CF} \cdot \Delta \frac{CF_{i,t}}{PPE_{i,t-1}} + \varepsilon_{i,t} \quad (3)$$

where $\Delta X = X^{BB+} - X^{BBB-}$ is the difference in firm characteristic X between matched BB+ and BBB- firms. We use the procedure developed by Thompson (2010) to cluster the standard errors by both firm and quarter.

Examining the results in column 1, the coefficient on flows is positive and statistically significant. A one standard deviation increase in high-yield flows increases the investment of BB+ firms relative to the investment of matched BBB- firms by 0.020, or about 10% of their mean investment rate. The constant term is close to zero and not statistically significant, indicating that on average matched firms have similar investment rates.

In columns 2 and 3 we exclude the financial crisis period (2008-2010) and the period around the collapse of Drexel Burnham Lambert (1988-1992). The coefficient on flows is unchanged, showing that our results are not driven by a single episode. Instead, we are documenting the effects on firm investment of recurring capital shocks to high-yield mutual funds.

In column 4, we conduct a falsification test, adding *investment-grade* mutual fund flows as a regressor. We expect the coefficient on investment-grade flows to be small and insignificant for two reasons. First, our discussion of institutional restrictions suggests that investment-grade mutual fund flows should not affect the supply of capital available to speculative-grade firms. Second, investment-grade flows should not affect the investment of investment-grade firms very much because they have access to a much wider variety of financing sources than speculative-grade firms do. Thus, neither firm in a matched pair should be affected by investment-grade flows. In column 4, we see that the coefficient is indeed small and insignficant.

In column 5, we use the sample of BB+ firms with positive outlooks. The constant term is positive and statistically significant at 10%, indicating that on average these firms invest more than their BBB- matches. The sample size is less than one-seventh of the full sample; and so with the exception of Q which is now statistically significant at 10% instead of 1%, the other coefficients are no longer statistically significant. The point estimates, however, are remarkably similar, suggesting that the investment of BB+ firms with positive outlooks is similarly sensitive to high-yield fund flows.

Overall, Table 3 shows a statistically significant and economically meaningful effect of high-yield fund flows on the investment of BB+ firms relative to similar firms rated BBB-.

B.1 Results are robust to alternative matching procedures

In untabulated results we show that our findings are robust to alternative matching procedures. We examine a variety of different procedures, varying the procedure along three primary dimensions. First, we experiment with different metrics to measure the distance between firm characteristics, using the Euclidean distance metric and the propensity-score instead of the Mahalobnis metric utilized in the baseline. Next we try different sets of matching variables, including log assets, book and market leverage, Q, cash holdings, tangibility, z-score, sales growth, and ROA. Finally, we examine different match quality restrictions, requiring the characteristics of matched firms to be within half a standard deviation of each other rather than a full standard deviation. The results remain quantitatively, qualitatively, and statistically similar for all variations of our baseline matching procedure.

C Results are robust to controlling for macro variables

Our results so far indicate that the investment of BB+ firms is more sensitive to flows into high-yield mutual funds than the investment of matched BBB- firms. Our identifying assumption is that firms close to the investment-grade cutoff are subject to similar investment opportunities shocks. If this assumption holds, the differential sensitivity of investment to high-yield mutual fund flows is evidence of the real effects of capital supply shocks in the presence of market segmentation. Our matching procedure is designed to ensure that the identifying assumption holds so that our interpretation is valid.

However, there may still be concerns that the investment opportunities of matched firms are not quite the same, invalidating our interpretation of the results. A natural alternative is that the investment opportunities of lower-rated firms are more sensitive to the business cycle and that high-yield fund flows are picking up this greater sensitivity.

We address this possibility by directly controlling for a number of macroeconomic variables.[17] The variables we control for are the level of the VIX, the term spread, the Baa-Aaa credit spread, the aggregate stock market return, and GDP growth. We measure these variables as of quarter $t-1$, but our results are robust to using average values over the four quarters $[t-4, t-1]$ or to using contemporaneous values.

Table 4 presents the results. The first column shows the basic results in this specification without controlling for any macro variables. The next five columns control for each macro variable individually. None of the macro variables comes in significantly, and the coefficients on flows are significant and of similar magnitudes to our previous results. The final column controls for all of our macro variables simultaneously. Again, the coefficient on flows is unaffected. If anything, the results are slightly stronger when controlling for all macro variables. Thus, it seems unlikely that the differential sensitivity of BB+ investment to fund flows is driven by macroeconomic factors.

D No differential sensitivity to flows around other cutoffs

Next we conduct falsification tests using matched firm pairs around other rating cutoffs. If the BB+ firms in our sample differed from their BBB- matches along unobservable firm characteristics known to the rating agencies, we would expect firms to differ along those unobservable characteristics around every other rating cutoff as well. Thus, if our results were driven by such unobservable firm characteristics, we would expect to find differential investment sensitivities driven by the same unobservable characteristics around every cutoff. To test this hypothesis, for each credit rating cutoff from A through B we match firms just below the cutoff with firms just above the cutoff that are in the same industry, and have similar size, market leverage, z-score, Q, cash holdings, and sales growth. For example, we match firms rated A with firms rated A+. As there are few firms rated above A+ or below B, we do not report the results for cutoffs above A and below B.[18]

Each column of Table 5 reports the results of our placebo regressions for firms with the credit rating specified by column heading and matched to firms rated one notch higher. The results show that the investment-grade cutoff is the only one where there is a differential sensitivity of investment to high-yield mutual fund flows. This suggests that our results are not driven by differences in matched firm characteristics that are unobservable to us but known to the credit rating agencies.[19] Of course, we cannot completely rule out the possibility that special information known to the rating agencies is correlated with investment opportunities only at the investment-grade cutoff. However, our results on a) BB+ firms with positive outlook, whose information content is basically the same as of the BBB- rating, b) the insensitivity of the difference in the investment rates to macroeconomic variables, and c) higher sensitivity of firms without access to other financing sources, which we discuss next, help to alleviate such concerns.

Taken together, the last two sections suggest that our results are not driven by differences in investment opportunities between firms within a matched pair. While our analysis focuses on differencing out common shocks to firm demand for capital, the drivers of capital supply (i.e., fund flows) may also alleviate concerns about differential investment opportunities for two reasons. First, high-yield fund flows are dominated by retail investors. According to the Investment Company Institute retail funds made up 97.5% of all high-yield mutual fund assets in 1996 (the furthest the data goes back). Institutional asset share grows slowly over time, reaching 25% at the end of our sample period. Frazzini and Lamont (2008) use retail mutual fund flows as a measure of investor sentiment, and show that fund flows predict low subsequent returns, suggesting that retail investors do not have precise information about firm investment opportunities.[20] Second, BB+ firms constitute only 11% of all speculative-grade firms. Thus, fund flows are likely to be driven by the investment prospects of and possibly investor sentiment for lower-rated firms, which are very different from BB+ firms on observable characteristics.[21]

E Higher sensitivity of firms without access to other financing sources

Are certain types of firms more sensitive to high-yield fund flows? In principle, financially constrained firms with limited access to other sources of financing should be more sensitive to flows into high-yield mutual funds. We consider several proxies for financial constraints that have been put forward by the literature: firms that do not pay dividends (Fazzari, Hubbard, and Petersen, 1988; Baker, Stein, and Wurgler, 2003), firms with low cash flow from operations and high dependence on external financing (Rajan and Zingales, 1998), and firms with a high cash flow sensitivity of cash (Almeida, Campello, and Weisbach, 2004). On the other hand, the investment of firms that can borrow from banks or have access to the asset-backed securities market should be less sensitive to fund flows.

Table 6 tests these ideas by estimating our investment regressions for six different sample splits. In columns 1 and 2, we split BB+ firms by whether they pay dividends. For dividend paying firms, there is no differential sensitivity of investment to fund flows between BB+ and BBB- firms. The investment of BB+ firms that do not pay dividends, on the other hand, is strongly sensitive to high-yield fund flows. The coefficient on flows for these firms is 0.045, more than twice the coefficient in our benchmark regression. Note that our methodology is somewhat different than the typical cross-sectional analysis. We are keeping matched pairs together, but splitting the sample of matched pairs based on BB+ firm characteristics.

We next split BB+ firms by their cash flow from operations in columns 3 and 4. We find that the investment of BB+ firms with low cash flow is sensitive to high-yield fund flows, while the investment of BB+ firms with high cash flow is not. Although we cannot reject that the two coefficients are the same, it is encouraging that the effect of fund flows is stronger in the sample of low cash flow BB+ firms.

In columns 5 and 6 we split BB+ firms by their Rajan and Zingales (1998) measure of external dependence, which is meant to capture at the industry level the share of capital expenditures that is financed externally versus using internal cash flow.[22] BB+ firms in the top twenty industries by external dependence exhibit a higher sensitivity to high-yield fund flows than do firms outside the top twenty, though the point estimates are not statistically significant. Still, this cross-sectional split is a useful complement to the others, since a firm's industry cannot reveal anything about its credit quality relative to a matched firm in the same industry.

Next, we measure firms' ability to borrow from banks by whether they have a bank loan rating.[23] Such firms should find it easier to substitute to bank loans or the syndicated loan market when high-yield fund flows are low. This is what we find in columns 7 and 8. The investment of firms with a loan rating is not sensitive to fund flows, but the investment of firms without a loan rating is.

In columns 9 and 10 we split firms by whether they have access to the asset-backed securities market. Issuing asset- or mortgage-backed securities through a bankruptcy-remote trust can allow firms to tap investment-grade sources of financing. Since certain assets are much easier to securitize than others, access to the asset-backed securities market depends on the nature of firm assets. For instance, credit cards, car loans, and certain types of machinery and equipment are easier to borrow against in the asset-backed securities market. We therefore measure firms' ability to substitute to the asset-backed market by whether they are in an industry with significant issuance of asset- and mortgage-backed securities. The top five industries by ABS issuance (Electrical Equipment, Personal Services, Automobiles and Trucks, Machinery, and Retail) are the only ones where ABS makes up more than 10% of total issuance, therefore we label firms as having access to the asset-backed market if they are in the top five.

The results in columns 9 and 10 indicate that the investment of firms in the top five ABS industries is not sensitive to high-yield mutual fund flows. In fact the coefficient on fund flows is negative but not statistically significant. It is the investment of firms in industries that are not significant ABS issuers that responds to fund flows.

Finally, in columns 11 and 12 we split firms by their cash flow sensitivity of cash. Because we estimate cash flow sensitivity of cash for each firm, we do not have sufficient amount of nonoverlapping data and are forced to use the same 1986Q1-2010Q4 sample period. As a result our estimated cash flow sensitivities of cash and hence our sample splits could be subject to a forward-looking bias and should be interpreted with caution. Nevertheless, the results show that the investment of firms with a low cash flow sensitivity of cash, which should not be financially constrained, does not respond to high-yield mutual fund flows. In contrast, the investment of firms with a high sensitivity, which are likely to be financially constrained, responds strongly to fund flows.

Taken together, our results in Table 6 indicate that the investment of firms with limited ability to substitute away from the high-yield market responds strongly to flows into high-yield mutual funds, while the investment of other firms is generally not affected.

F BB+ bond issuance is more sensitive to flows than BBB- bond issuance

So far we have explored the connection between high-yield fund flows and firm investment without documenting a particular mechanism. In this section, we document the effect of fund flows on bond issuance.[24] We continue to use the same empirical methodology, regressing the difference in the bond issuance of matched BB+ and BBB- firms on high-yield mutual fund flows.

Table 7 presents the results. The first column shows that BB+ issuance is more sensitive to high-yield fund flows that BBB- issuance. A one-standard deviation increase in flows increases issuance (as a fraction of assets) by 0.30%, relatively to the mean issuance rate of 0.56%. Our power is somewhat limited since there are only 46 BB+ issuance events and 61 BBB- issuance events in our data. However, the coefficient on flows is still statistically significant. The second and third columns show the results are robust to excluding the financial crisis period (2008-2010) and the period around the collapse of Drexel Burnham Lambert (1988-1992) respectively. Finally, column 4 shows that the results are robust to controlling for macro variables.

Thus, it appears that bond issuance does play an important role in connecting high-yield mutual fund flows to the investment of BB+ firms.[25]

V Conclusion

The sharp distinction drawn between investment- and speculative-grade firms is one of the most salient features of credit markets. These terms are more than convenient labels—we show that this segmentation has significant consequences for firm investment.

Our paper makes three contributions. First, we show that BB+ firms and their BBB- matches on average have similar investment rates, suggesting that the average allocation of capital is efficient across segments. Second, we find that flows into high-yield mutual funds increase the investment of BB+ firms relative to their BBB- matches. Thus, the interaction of market segmentation and financial market conditions exposes firms to non-fundamental variation in the availability and cost of capital, which in turn leads to excess volatility in their investment. This is particularly true for firms that do not have access to other sources of financing. Third, we show that flows also increase BB+ bond issuance, suggesting that the availability of capital is an important driver of investment.

The distortions induced by fund flows are economically meaningful but not excessively large. However, our estimates are likely to be a lower bound because the firms facing the largest costs of a BB+ rating are likely to alter their behavior to obtain a BBB- rating. By highlighting the distortionary effects of rules and regulations tied to credit ratings on firm investment, our work contributes to the policy debate surrounding the role of credit ratings. In the aftermath of the financial crisis, it is particularly important to understand interactions between financial frictions and the real economy. Distortions like the ones we document may be particularly important in economic downturns, when they can amplify shocks to the real economy.

However, our results should not be interpreted as suggesting that credit ratings are not valuable, or that the division of the corporate bond market into two grades is not efficient in a broader sense. Credit ratings carry information and may help investors economize on information production costs and manage agency problems between investors and fund managers. What we want to emphasize is that sharp divides can have significant, recurring, time-varying effects on real investment that should be weighed carefully against any potential benefits.

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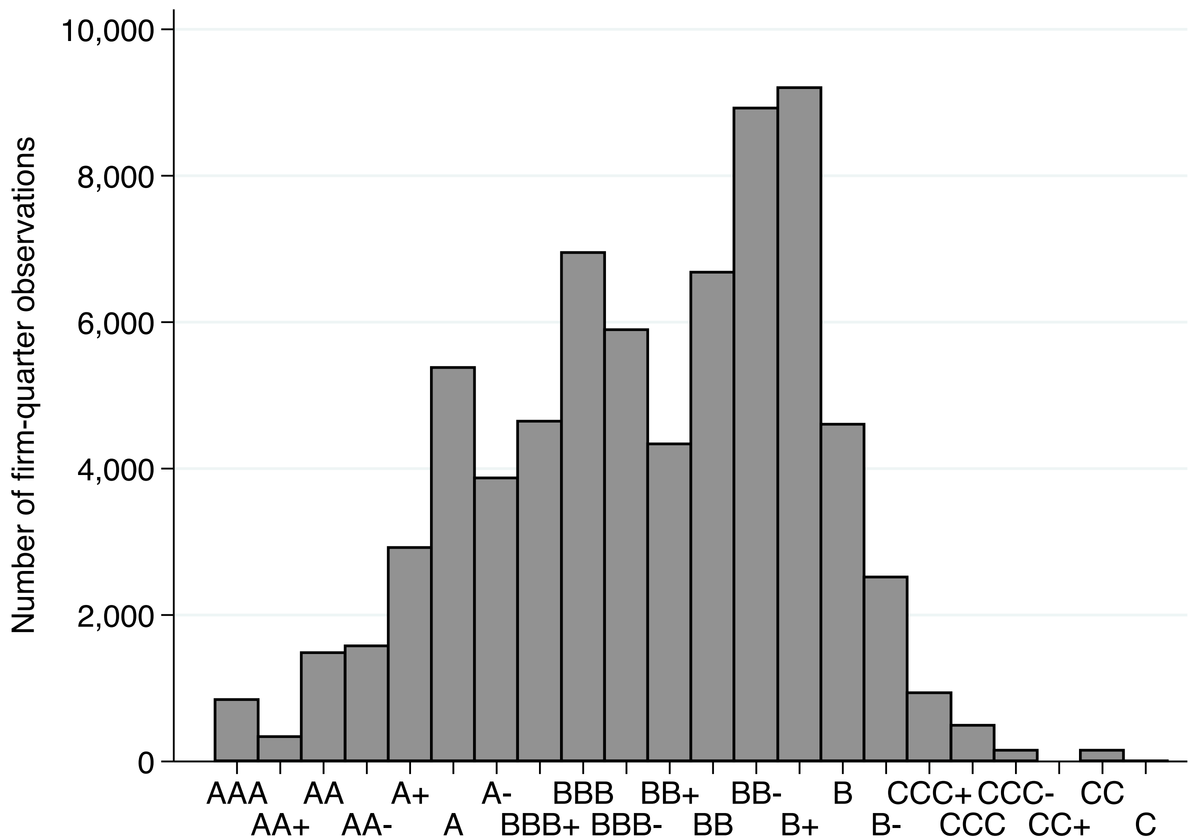

Figure 1
Distribution of Issuer Credit Ratings

This figure shows the distribution of S&P domestic long-term issuer credit rating for firms in the quarterly CRSP/Compustat merged data set, excluding financials and utilities. The sample period is 1986Q1-2010Q4.

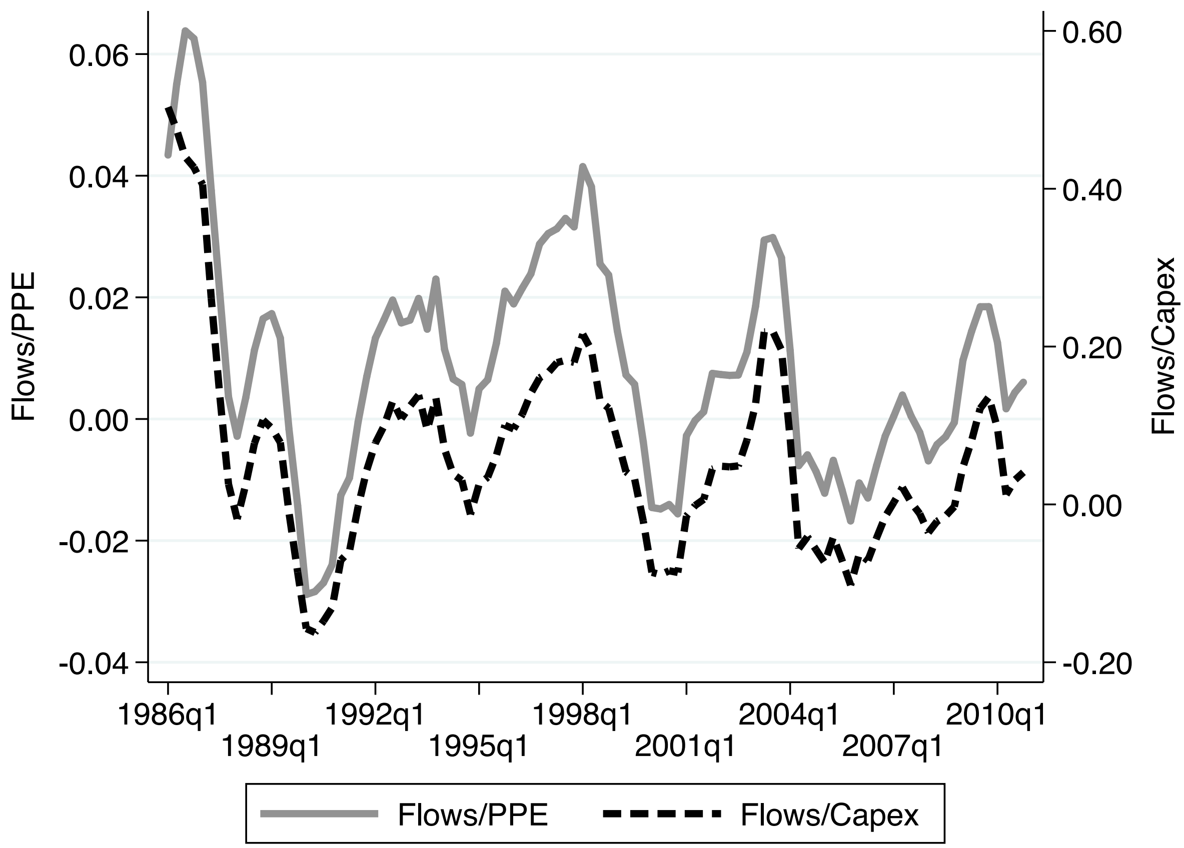

Figure 2
High-Yield Mutual Fund Flows relative to PPE and Capex of BBB and BB Firms

This figure shows the time-series of flows into high-yield mutual funds. Monthly aggregate flows into high-yield mutual funds are from the Investment Company Institute. Cumulative high-yield fund flows calculated over four quarters are scaled by either total PPE or cumulative capital expenditures over four quarters of CRSP/Compustat firms rated BBB+ through BB-, excluding financials and utilities. The sample period is 1986Q1-2010Q4.

Table 1
Means of Firm Characteristics by Credit Rating

	Investment Grade									Speculative Grade						
	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC
Assets	28778	20085	13705	13025	11536	9550	8670	6404	5864	4035	2779	2031	1466	2155	1969	1540
Book leverage	0.265	0.321	0.341	0.359	0.386	0.382	0.409	0.440	0.455	0.479	0.535	0.577	0.657	0.743	0.754	0.906
Market leverage	0.119	0.135	0.151	0.169	0.201	0.229	0.244	0.291	0.308	0.335	0.378	0.427	0.490	0.558	0.565	0.674
Z-score	1.304	1.200	1.207	1.208	1.094	1.007	0.906	0.882	0.844	0.762	0.682	0.577	0.406	0.038	−0.175	−0.581
Interest coverage	27.161	17.035	15.030	14.217	11.540	10.051	9.082	7.128	7.142	6.166	4.929	4.261	2.130	0.904	−0.489	−0.887
Cash/Assets	0.091	0.079	0.068	0.069	0.070	0.065	0.063	0.061	0.069	0.069	0.075	0.081	0.094	0.119	0.151	0.108
PPE/Assets	0.374	0.399	0.348	0.345	0.347	0.368	0.389	0.365	0.341	0.372	0.354	0.351	0.341	0.364	0.352	0.405
Q	2.461	2.411	2.193	2.078	1.939	1.766	1.745	1.557	1.563	1.515	1.493	1.455	1.404	1.414	1.478	1.415
Operating margin	0.244	0.209	0.184	0.191	0.183	0.183	0.195	0.159	0.166	0.172	0.169	0.178	0.145	0.110	0.028	0.030
ROA	0.103	0.093	0.080	0.079	0.068	0.059	0.055	0.045	0.042	0.037	0.031	0.018	−0.003	−0.043	−0.085	−0.137
CF/PPE	0.594	0.519	0.515	0.549	0.475	0.523	0.446	0.442	0.539	0.478	0.545	0.424	0.349	0.114	−0.183	−0.346
Capex/PPE	0.220	0.214	0.215	0.213	0.208	0.220	0.221	0.198	0.213	0.217	0.242	0.241	0.249	0.259	0.255	0.165
Sales growth	0.088	0.084	0.074	0.078	0.089	0.100	0.114	0.093	0.107	0.138	0.153	0.177	0.199	0.207	0.204	0.116

This table reports the means of firm characteristics by credit rating for our sample of firms in the quarterly CRSP/Compustat merged data set, excluding financials and utilities. The sample period is 1986Q1-2010Q4. Variable definitions are in the Appendix Table 8.

Table 2
Characteristics of Matched BB+ and BBB- Firms

	Full sample			Matched sample			BB+ with positive outlook		
	BBB-	BB+	Δ	BBB-	BB+	Δ	BBB-	BB+	Δ
Assets	5864	4035	-1829^{***}	4072	3889	-183	5159	5006	-153
Book leverage	0.455	0.479	0.024	0.437	0.453	0.017	0.444	0.425	-0.019
Market leverage	0.308	0.335	0.028^{**}	0.321	0.327	0.005	0.289	0.268	-0.021
Z-score	0.844	0.762	-0.082^{**}	0.853	0.845	-0.008	0.811	0.774	-0.036
Interest coverage	7.142	6.166	-0.976	6.000	5.532	-0.468	6.501	6.066	-0.436
Cash/Assets	0.069	0.069	-0.000	0.043	0.045	0.002	0.041	0.043	0.001
PPE/Assets	0.341	0.372	0.031^{*}	0.370	0.356	-0.013	0.408	0.368	-0.039
Q	1.563	1.515	-0.048	1.351	1.372	0.020	1.473	1.554	0.081
Operating margin	0.166	0.172	0.005	0.169	0.166	-0.003	0.184	0.181	-0.003
ROA	0.042	0.037	-0.004	0.039	0.040	0.001	0.038	0.054	0.016^{*}
CF/PPE	0.539	0.478	-0.060	0.484	0.480	-0.003	0.378	0.491	0.114
Capex/PPE	0.213	0.217	0.004	0.201	0.205	0.005	0.189	0.254	0.065^{**}
Sales growth	0.107	0.138	0.031	0.113	0.128	0.015	0.143	0.167	0.023

This table reports the characteristics of matched BB+ and BBB- firms. Each quarter a given BB+ firm is matched to a BBB- firm that is within the same Fama-French 48 industry and is closest in terms of log assets, market leverage, Q, cash-to-assets ratio, z-score, and sales growth. We measure distance using the Mahalanobis metric, and require the difference in each matching variable to be smaller than one standard deviation of that variable. The full sample consists of 4,331 BB+ and 5,897 BBB- firm-quarter observations. The matched sample consists of 1,056 BB+ firm-quarter observations matched to 883 unique BBB- firm-quarter observations. The sample of BB+ firms with positive outlooks consists of 143 BB+ firm-quarter observations matched to 131 unique BBB- firm-quarter observations. The sample period is 1986Q1-2010Q4. Standard errors are adjusted for clustering by firm. *, **, and *** denote statistical significance at 10%, 5%, and 1%.

Table 3
Difference in the Investment Rates of Matched Firms and High-Yield Fund Flows

	(1)	(2)	(3)	(4)	(5)
$\Delta Q_{i,t-1}$	0.102***	0.110***	0.104***	0.102***	0.108*
	(0.030)	(0.033)	(0.030)	(0.030)	(0.057)
$\Delta \frac{CF_{i,t}}{PPE_{i,t-1}}$	0.039***	0.046***	0.038***	0.039***	0.034
	(0.012)	(0.018)	(0.012)	(0.012)	(0.022)
High-yield fund flows$_{t-1}$	0.020**	0.021**	0.021**	0.022**	0.026
	(0.009)	(0.009)	(0.009)	(0.009)	(0.022)
Investment-grade fund flows$_{t-1}$				−0.006	
				(0.008)	
Constant	0.002	0.002	0.000	0.002	0.051*
	(0.010)	(0.011)	(0.010)	(0.010)	(0.026)
N	1056	888	982	1056	143
Adjusted R^2	0.088	0.091	0.094	0.088	0.052
Notes		excluding 2008 crisis (2008-2010)	excluding collapse of Drexel (1988-1992)		BB+ firms with positive outlooks

This table reports the results of the regressions of the difference in the investment rates of matched BB+ and BBB- firms on high-yield fund flows

$$\Delta \frac{CAPX_{i,t}}{PPE_{i,t-1}} = \alpha + \beta_{Flows} \cdot \textit{High-yield fund flows}_{t-1} + \beta_Q \cdot \Delta Q_{i,t-1} + \beta_{CF} \cdot \Delta \frac{CF_{i,t}}{PPE_{i,t-1}} + \varepsilon_{i,t}$$

where $\Delta X = X^{BB+} - X^{BBB-}$ is the difference in firm characteristic X between matched BB+ and BBB- firms. The sample period is 1986Q1-2010Q4 unless noted otherwise. Cumulative high-yield mutual fund flows over the four quarters $[t-4, t-1]$ are scaled by the total PPE of all firms rated BBB+ through BB-, PPE_{t-1}. The value of fund flows is standardized so that the coefficient on flows represents the effect of one standard deviation change in fund flows. Standard errors are adjusted for clustering by both firm and quarter using Thompson (2010). *, **, and *** denote statistical significance at 10%, 5%, and 1%.

Table 4
Controlling for Macroeconomic Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta Q_{i,t-1}$	0.102***	0.102***	0.101***	0.102***	0.102***	0.102***	0.100***
	(0.030)	(0.030)	(0.029)	(0.030)	(0.030)	(0.030)	(0.030)
$\Delta \frac{CF_{i,t}}{PPE_{i,t-1}}$	0.039***	0.039***	0.038***	0.039***	0.039***	0.039***	0.039***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
High-yield fund flows$_{t-1}$	0.020**	0.020**	0.023***	0.020**	0.021**	0.020**	0.024***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
VIX$_{t-1}$		0.003					0.000
		(0.007)					(0.011)
Term spread$_{t-1}$			−0.013				−0.016
			(0.009)				(0.010)
Credit spread$_{t-1}$				0.000			0.007
				(0.008)			(0.010)
Stock market return$_{t-1}$					−0.003		−0.005
					(0.005)		(0.006)
GDP growth$_{t-1}$						0.001	0.004
						(0.008)	(0.007)
Constant	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
N	1056	1052	1056	1056	1056	1056	1052
Adjusted R^2	0.088	0.087	0.091	0.087	0.087	0.087	0.090

This table reports the results of the regressions of the difference in the investment rates of matched BB+ and BBB- firms on high-yield fund flows and macroeconomic variables

$$\Delta \frac{CAPX_{i,t}}{PPE_{i,t-1}} = \alpha + \beta_{Flows} \cdot \textit{High-yield fund flows}_{t-1} + \beta_Q \cdot \Delta Q_{i,t-1} + \beta_{CF} \cdot \Delta \frac{CF_{i,t}}{PPE_{i,t-1}} + \varepsilon_{i,t}$$

where $\Delta X = X^{BB+} - X^{BBB-}$ is the difference in firm characteristic X between matched BB+ and BBB- firms. Macroeconomic variables are defined in Appendix Table 8, and are standardized so that the coefficients represent the effect of one standard deviation change in the explanatory variables. The sample period is 1986Q1-2010Q4. Standard errors are adjusted for clustering by both firm and quarter using Thompson (2010). *, **, and *** denote statistical significance at 10%, 5%, and 1%.

Table 5
Placebo Regressions

	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B
$\Delta Q_{i,t-1}$	0.031**	0.073***	0.052***	0.016	0.061***	0.102***	0.082***	0.113***	0.095***	0.143***
	(0.015)	(0.021)	(0.019)	(0.019)	(0.017)	(0.030)	(0.021)	(0.022)	(0.021)	(0.020)
$\Delta \frac{CF_{i,t}}{PPE_{i,t-1}}$	0.035*	0.005	0.038*	0.067***	0.055***	0.039***	0.060***	0.056***	0.050***	0.020
	(0.021)	(0.041)	(0.022)	(0.021)	(0.021)	(0.012)	(0.014)	(0.012)	(0.010)	(0.013)
High-yield fund flows$_{t-1}$	0.003	−0.002	−0.010	0.004	−0.004	0.020**	−0.004	−0.003	0.006	−0.001
	(0.006)	(0.008)	(0.007)	(0.005)	(0.006)	(0.009)	(0.009)	(0.008)	(0.009)	(0.010)
Constant	0.011*	0.019**	−0.008	−0.017**	0.004	0.002	0.025**	−0.000	−0.001	0.021**
	(0.007)	(0.009)	(0.010)	(0.007)	(0.007)	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)
N	664	572	746	1177	1159	1056	1219	2341	2758	1536
Adjusted R^2	0.027	0.046	0.030	0.039	0.070	0.088	0.069	0.059	0.053	0.054

This table reports the results of the placebo regressions of the difference in the investment rates of matched firms around other credit rating cutoffs on high-yield fund flows

$$\Delta \frac{CAPX_{i,t}}{PPE_{i,t-1}} = \alpha + \beta_{Flows} \cdot \textit{High-yield fund flows}_{t-1} + \beta_Q \cdot \Delta Q_{i,t-1} + \beta_{CF} \cdot \Delta \frac{CF_{i,t}}{PPE_{i,t-1}} + \varepsilon_{i,t}$$

where $\Delta X = X^R - X^{\hat{R}}$ is the difference in firm characteristic X between firms rated R and matched firms rated one notch higher, $\hat{R}$. In each column the sample consists of firms specified by the column name and matched firms rated one notch higher. For example, the sample in the first column is firms rated A and matched firms rated A+. Firms are matched using the Mahalanobis metric on log assets, market leverage, Q, cash-to-assets, z-score, and sales growth within Fama-French 48 industries. We require the difference in each matching variable to be less than one standard deviation of that variable. The sample period is 1986Q1-2010Q4. Cumulative high-yield mutual fund flows over the four quarters $[t-4, t-1]$ are scaled by the total PPE of all firms rated BBB+ through BB-, PPE_{t-1}. The value of fund flows is standardized so that the coefficient on flows represents the effect of one standard deviation change in fund flows. Standard errors are adjusted for clustering by both firm and quarter using Thompson (2010). *, **, and *** denote statistical significance at 10%, 5%, and 1%.

Table 6
Cross-Sectional Splits

	Dividend Payer		Low Cash Flow		Top 20 External Dependence Industry		Bank Loan Rating		Top 5 ABS Industry		High Cash Flow Sensitivity of Cash	
	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	No	Yes
$\Delta Q_{i,t-1}$	0.055	0.143***	0.152***	0.051	0.161***	−0.001	0.115***	0.140**	0.068**	0.122***	0.049	0.115***
	(0.038)	(0.040)	(0.045)	(0.035)	(0.038)	(0.036)	(0.039)	(0.062)	(0.031)	(0.038)	(0.034)	(0.039)
$\Delta \frac{CF_{i,t}}{PPE_{i,t-1}}$	0.040***	0.036*	−0.004	0.058***	0.045*	0.040***	0.048*	−0.036	0.028***	0.042***	0.021	0.065***
	(0.012)	(0.019)	(0.018)	(0.012)	(0.027)	(0.009)	(0.029)	(0.061)	(0.009)	(0.015)	(0.014)	(0.009)
High-yield fund flows$_{t-1}$	0.002	0.045***	0.029**	0.009	0.028	0.012	0.014	0.035*	−0.009	0.031***	0.004	0.027**
	(0.009)	(0.015)	(0.013)	(0.010)	(0.018)	(0.007)	(0.011)	(0.020)	(0.011)	(0.011)	(0.008)	(0.012)
Constant	−0.017	0.029*	−0.008	0.005	−0.014	0.021**	0.001	−0.000	−0.014	0.010	−0.016	0.003
	(0.011)	(0.017)	(0.012)	(0.015)	(0.017)	(0.010)	(0.015)	(0.020)	(0.015)	(0.013)	(0.012)	(0.015)
N	632	418	528	528	486	570	541	180	284	772	513	524
Adjusted R^2	0.053	0.145	0.096	0.112	0.130	0.063	0.077	0.102	0.095	0.099	0.026	0.140

This table reports the results of the regressions of the difference in the investment rates of matched BB+ and BBB- firms on high-yield fund flows

$$\Delta \frac{CAPX_{i,t}}{PPE_{i,t-1}} = \alpha + \beta_{Flows} \cdot \textit{High-yield fund flows}_{t-1} + \beta_Q \cdot \Delta Q_{i,t-1} + \beta_{CF} \cdot \Delta \frac{CF_{i,t}}{PPE_{i,t-1}} + \varepsilon_{i,t}$$

estimated separately for subsamples of BB+ firms split by dividends, cash flows, external dependence, having a bank loan rating, access to the asset-backed securities market, and cash flow sensitivity of cash. $\Delta X = X^{BB+} - X^{BBB-}$ is the difference in firm characteristic X between matched BB+ and BBB- firms. Dividend payers are firms with positive cash dividends. Low cash flow firms are the ones below the median of the cash-to-assets ratio for BB+ firms. Rajan and Zingales (1998) measure of external dependence is calculated using annual Compustat data for the 1970-1985 period. Bank loan rating indicates the existence of a bank loan rating. Top 5 industries by the share of asset- and mortage-backed securities issuance in total industry-level bond issuance are Electrical Equipment, Personal Services, Automobiles and Trucks, Machinery, and Retail. The sample period is 1986Q1-2010Q4 in all regressions except for the bank loan rating split, where the sample period is 1986Q1-2005Q2. Standard errors are adjusted for clustering by both firm and quarter using Thompson (2010). *, **, and *** denote statistical significance at 10%, 5%, and 1%.

Table 7
Bond Issuance by Matched Firms and Fund Flows

	(1)	(2)	(3)	(4)
High-yield fund flows$_{t-1}$	0.003**	0.003**	0.003**	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
VIX$_{t-1}$				−0.002
				(0.002)
Term spread$_{t-1}$				−0.000
				(0.002)
Credit spread$_{t-1}$				−0.002
				(0.002)
Stock market return$_{t-1}$				−0.001
				(0.001)
GDP growth$_{t-1}$				−0.001
				(0.001)
Constant	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
N	1056	888	982	1052
Adjusted R^2	0.004	0.005	0.003	0.006
Notes		excluding 2008 crisis (2008-2010)	excluding collapse of Drexel (1988-1992)	

This table reports the results of the regressions of the difference in bond issuance by matched BB+ and BBB- firms on high-yield fund flows

$$\Delta Issuance_{i,t} = \alpha + \beta_{Flows} \cdot \textit{High-yield fund flows}_{t-1} + \varepsilon_{i,t}$$

Issuance of non-convertible, not asset- or mortgage-backed bonds from SDC is scaled by lagged assets. Cumulative high-yield mutual fund flows over the four quarters $[t-4, t-1]$ are scaled by the total assets of all firms rated BBB+ through BB-, $Assets_{t-1}$. The value of fund flows is standardized so that the coefficient on flows represents the effect of one standard deviation change in fund flows. The sample period is 1986Q1-2010Q4, except for columns 2 and 3. In column 2, the sample period excludes the 2008-2010 period around the 2008 financial crisis. In column 3, the sample period excludes the 1988-1992 period around the collapse of Drexel Burnham Lambert. Standard errors are adjusted for clustering by both firm and quarter using Thompson (2010). *, **, and *** denote statistical significance at 10%, 5%, and 1%.

Notes

[1] See, for example, Bernanke and Blinder (1992), Kashyap, Stein, and Wilcox (1993), Slovin, Sushka, and Polonchek (1993), Gertler and Gilchrist (1994), Bernanke and Gertler (1995), Kashyap and Stein (2000), Peek and Rosengren (2000), Khwaja and Mian (2008), and Leary (2009).

[2] See, for example, Benston and Kaufman (1997), Benveniste, Singh, and Wilhelm (1993), Brewer III and Mondschean (1994), and Carey, Prowse, Rea, and Udell (1993).

[3] See, for example, Sufi (2009), Kisgen and Strahan (2010), and Tang (2009) in addition to Lemmon and Roberts (2010).

[4] The act prohibited purchases of speculative-grade bonds and mandated existing holdings to be liquidated by 1994. As a result, thrifts' share of the corporate bond market fell from around 7% in 1988 to less than 1% by 2010 (Flow of Funds Accounts of the United States, Table L212, Corporate and Foreign Bonds).

[5] Risk charges for A, BBB, BB, and B rated bonds are 0.4%, 1.3%, 4.6%, and 10% respectively. The portfolio share of all non-investment grade bonds is capped at 20%. As a result of these restrictions, insurance companies' share of all speculative-grade bonds is only 8.5%, one-fourth of their 34% share of all investment-grade bonds (Ellul, Jotikasthira, and Lundblad, 2011).

[6] Haircuts for investment-grade nonconvertible debt securities paying a fixed interest rate vary between 2% and 9% depending on maturity. Haircuts for speculative-grade bonds are generally 15%.

[7] For consistency of exposition, we use Standard & Poor's rating scale throughout the paper.

[8] As Poor's Publishing, Standard Statistics, and Fitch Publishing entered the credit ratings market in 1916, 1922, and 1924, they generally followed similar characterizations. All agencies described BB as either "Good" or "Fair," and none referred to it as speculative (Harold, 1938).

[9]Although the ruling applied only to national banks, many state banking regulators followed the Comptroller's lead and introduced similar restrictions for state chartered banks.

[10]There is still considerable debate, however, as to whether credit ratings contain any information not already available to investors. Market-based measures of credit quality tend to be better predictors of default than credit ratings, at least at short- and medium-term horizons (Cantor and Mann, 2006). Kliger and Sarig (2000) and Tang (2009) argue that Moody's refinement of its rating system revealed new information about rated firms. Jorion, Liu, and Shi (2005) find greater informational effects of credit rating changes after Regulation Fair Disclosure prohibited companies from selectively disclosing nonpublic information, but excluded rating analysts from the new regulation.

[11]For a review of matching estimators see Imbens (2004) and Abadie and Imbens (2006).

[12]To make our results more comparable with papers using annual data, we annualize investment and cash flow.

[13]The two primary exceptions are obtaining a guarantee from another entity and issuing asset-backed securities.

[14]In untabulated results we estimate that approximately 10% of all nonconvertible bond issues (weighted by proceeds) by non-financial firms are notched up. The vast majority of notched up issues are asset- and mortgage-backed bonds.

[15]In untabulated results, we do not find any differences in corporate governance, as measured by the G Index (Gompers, Ishii, and Metrick, 2003) and its components, between the matched BB+ and BBB- firms.

[16]In this subsample, we match 143 BB+ observations to 131 unique BBB- firm-quarter observations.

[17] Our results are also robust to excluding the three recessions in our sample period.

[18]We find similar results, i.e., that investment of lower rated firms is not more sensitive to fund flows than investment of higher rated firms, for these other cutoffs.

[19]Note that the lack of statistically significant results around other cutoffs does not appear

to be due to smaller sample sizes and weaker power.

[20]Lee, Shleifer, and Thaler (1991) and Baker and Wurgler (2007) use the closed-end fund discount as a measure of investor sentiment. In untabulated results we find that high-yield mutual fund flows are strongly negatively correlated with the discount on closed-end high-yield funds, suggesting that fund flows might be driven by investor sentiment.

[21]For example, while average 5-year default rates for BBB- and BB+ firms are 3.93% and 5.89%, average 5-year default rates for BB-, B+, and B firms, which together account for more than 60% of the total number of speculative-grade firms, are 12.41%, 18.28%, and 26.03% (Standard & Poor's, 2010).

[22]To calculate industry external dependence we use nonoverlapping data from the 1970-1985 period to prevent the realizations of fund flows during our sample period from affecting our measures of external dependence. We get similar results, however, when using the same sample period to measure external dependence and estimate our investment regressions.

[23]Unfortunately, our data on bank loan ratings are limited to the 1986Q1-2005Q2 period.

[24]There is a growing literature documenting the effects of ratings on firm financing decisions. Faulkender and Petersen (2006) find that firms with a credit rating that allows them to access public debt markets have 35% more debt than other similar firms. Kisgen (2006) argues that firm financing decisions are affected by the discrete costs and benefits of different credit ratings. Sufi (2009) studies how the introduction of syndicated bank loan ratings by Moody's and Standard & Poor's in 1995 expanded the set of investors able to invest in syndicated loans and led to increased debt issuance and investment by lower-rated borrowers.

[25]In unreported regressions we estimate our investment regressions on the small sample of 46 BB+ firm-quarter observations with positive issuance activity. The coefficient on flows within this sample is three times the coefficient in the full sample, and has a p-value of 12%. This evidence is consistent with the link between firm investment and high-yield fund flows being strongest for firms that do issue.

VI Appendix

Table 8
Variable Definitions

Variable	Definition
ABS share	The share of asset- and mortage-backed bonds in total non-convertible bond issuance by Fama-French 48 industry. Non-convertible bond issuance by domestic publicly-traded firms is from SDC. Shelf registrations and initiations of medium-term note programs are excluded.
Book leverage	Book debt divided by the sum of book debt and stockholder equity.
Cash flow	Income before extraordinary items plus depreciation. Cash flow is annualized.
Cash flow sensitivity of cash	Cash flow sensitivity of cash is the coefficient on cash flow in the regression of the change in cash (scaled by assets) on cash flow, Q, and log assets (Almeida, Campello, and Weisbach, 2004). For each firm, we estimate the cash flow sensitivity of cash using quarterly data over the 1986Q1-2010Q4 sample period and requiring at least ten observations.
Credit spread	Difference in yields between Moody's Baa and Aaa rated industrial bonds. Average of the end-of-month values (from the Federal Reserve Statistical Release H.15 "Selected Interest Rates") during quarter t.
External dependence	Rajan and Zingales (1998) measure of external dependence, calculated at the Fama-French 48 industries level. Using annual Compustat data set covering the 1970-1985 period, we first calculate for each firm total capital expenditures minus total cash flows from operations during this period, all scaled by total capital expenditures. We then take the industry median as the industry measure of external dependence.
Flows$_{t-1}$	Monthly aggregate flows into high-yield mutual funds are from the Investment Company Institute. Cumulative flows over the four quarters $[t-4, t-1]$ are scaled by the total PPE of firms rated BBB+ through BB-, PPE_{t-1}. The value of fund flows is standardized so that the coefficient on flows represents the effect of a one standard deviation change in high-yield fund flows.
GDP growth	Percentage change during quarter t in the seasonally adjusted real GDP (from the Bureau of Economic Analysis).
Interest coverage	The ratio of EBIT to interest expense, calculated using four-quarter moving averages of EBIT and interest expense.
Investment	Capital expenditures scaled by lagged PPE, $\frac{CAPX_{i,t}}{PPE_{i,t-1}}$. Investment is annualized.
Market leverage	Book debt divided by the sum of book debt and market value of equity from CRSP.
Operating margin	Operating income before depreciation divided by sales.
Q	Market value of equity from CRSP plus assets minus the book value of stockholder equity, all divided by assets.
ROA	Income before extraordinary items divided by assets. ROA is annualized.
Sales growth	Percentage change in sales over the last four quarters.
Stock market return	Value-weighted return on all NYSE, AMEX, and NASDAQ stocks minus the 1-month T-Bill rate. Average of monthly values (from Kenneth French's website) during quarter t.
Term spread	Difference in yields between 10-year constant-maturity Treasuries and 3-month T-Bills. Average of the end-of-month values (from the Federal Reserve Statistical Release H.15 "Selected Interest Rates") during quarter t.
VIX	Chicago Board Options Exchange Volatility Index. Average of the end-of-month values (from Datastream) during quarter t.
Z-score	$1.2 \cdot WC_{i,t}/Assets_{i,t} + 1.4 \cdot RE_{i,t}/Assets_{i,t} + 3.3 \cdot EBIT_{i,t}/Assets_{i,t} + Sales_{i,t}/Assets_{i,t}$, where $WC_{i,t}$ is working capital, and $RE_{i,t}$ is retained earnings.We exclude leverage from the calculation of Z-score because we directly use leverage as one of the matching variables.