# Costly External Finance: Implications for Capital Markets Anomalies

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**Abstract**

In a frictionless world, investment is perfectly elastic to the discount rate. With frictions, investment is less elastic: a given magnitude of change in investment is associated with a higher magnitude of change in the discount rate, meaning that investment is a more powerful predictor of future stock returns. We document that the predictive power of investment-to-assets, asset growth, and investment growth for cross-sectional returns is significantly stronger in financially more constrained firms than in financially less constrained firms, but that the predictive power of net stock issues, abnormal corporate investment, and net operating assets is not. Investment frictions also provide an alternative interpretation for evidence commonly attributed to limits to arbitrage.

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# 1 Introduction

We derive and test a novel implication of $q$-theory on cross-sectional returns: the expected return-investment relation should be stronger in firms with high investment frictions than in firms with low investment frictions. Initiated by Cochrane (1991, 1996), investment-based asset pricing argues that real investment is important for determining expected returns. Intuitively, all else equal, low costs of capital mean high net present values of new projects and high investment, and high costs of capital mean low net present values of new projects and low investment. The literature has so far explored the broad-ranging implications of the negative expected return-investment relation.[1] By exploring the previously ignored interaction between this relation and investment frictions, our tests can potentially address whether these implications can indeed be attributed to $q$-theory.

Our economic idea is simple. In a perfect world without frictions, investment is infinitely elastic to changes in the discount rate, meaning that a small change in the discount rate is associated with an infinite magnitude of change in investment. With frictions, investment entails general investment costs, causing investment to be less elastic to changes in the discount rate. The more investment frictions a firm faces, the less elastic the firm's investment will be in responding to changes in the discount rate. Equivalently, a given change in investment will correspond to a higher magnitude of change in the discount rate, meaning that investment is a more powerful predictor of future returns.

Our test design is also simple. We identify investment frictions with firm-level proxies of financing constraints. The idea is that if there are investment costs such as adjustment costs of capital, frictions in capital markets induce additional financing costs at the margin. We use three financing constraints proxies: asset size, payout ratio, and bond ratings. Firms with small asset, low payout ratios, and unrated public debt are more financially constrained than firms with big asset, high payout ratios, and rated public debt, respectively. We connect optimal investment in theory with

[1] Cochrane (1991) shows that aggregate investment is a strong predictor of stock market excess returns. Cochrane (1996) uses residential and nonresidential investment growth as two factors to price the cross-section of returns. Zhang (2005) and Li, Livdan, and Zhang (2008) use dynamic investment models to understand the value anomaly and external financing anomalies, respectively. Anderson and Garcia-Feijóo (2006) show that investment growth is correlated with size and book-to-market. Li, Vassalou, and Xing (2006) use sectoral investment growth to price cross-sectional returns. Lyandres, Sun, and Zhang (2008) show that adding an investment factor into the CAPM and the Fama-French three-factor model substantially reduces the magnitude of the underperformance following initial public offerings, seasoned equity offerings, and convertible bond offerings. Xing (2008) shows that an investment growth factor explains the book-to-market effect roughly as well as Fama and French's (1993) value factor. Chen and Zhang (2009) show that real investment is the common driving force of a wide range of cross-sectional return anomalies such as reversal, sales growth, leverage, asset growth, and net stock issues. Liu, Whited, and Zhang (2009) derive and test implications of investment Euler equations for cross-sectional returns. Finally, Wu, Zhang, and Zhang (2009) show that capital investment helps explain the accrual anomaly.

six cross-sectional predictors of returns: Chen and Zhang's (2009) investment-to-assets, Cooper, Gulen, and Schill's (2008) asset growth, Xing's (2008) investment growth, Fama and French's (2008) net stock issues, Titman, Wei, and Xie's (2004) abnormal corporate investment, and Hirshleifer, Hou, Teoh, and Zhang's (2004) net operating assets. We run Fama-MacBeth (1973) cross-sectional regressions of returns on a given investment variable within extreme subsamples split by a given financing constraints proxy. Under the $q$-theory logic, the magnitude of the slope should be higher in firms with high investment frictions than in firms with low investment frictions.

The news is mixed for $q$-theory. The slopes of investment-to-assets, asset growth, and investment growth have significantly higher magnitude in more constrained firms than in less constrained firms. The investment-to-assets slope is $-1.02$ ($t=6.13$) in the low payout subsample (tercile) and $-0.34$ ($t = -1.85$) in the high payout subsample: the difference of $-0.68$ is more than three standard errors from zero. The asset growth slope is $-0.93$ ($t=-8.30$) in the small asset tercile and $-0.50$ ($t=-3.90$) in the big asset tercile: the difference of $-0.43$ is more than 2.7 standard errors from zero. The investment growth slope is $-0.11$ ($t=-6.53$) in firms without bond ratings and $-0.05$ ($t= -2.43$) in firms with bond ratings: the difference of $-0.06$ is more than 2.5 standard errors from zero.

However, the slopes of net stock issues, abnormal corporate investment, and net operating assets do not differ significantly across extreme constraints subsamples. The net stock issues slope is $-1.63$ in the small asset tercile and $-1.54$ in the big asset tercile: the difference of $-0.09$ is within 0.3 standard errors from zero. The abnormal corporate investment slope is $-0.10$ in the low payout tercile and $-0.02$ in the high payout tercile: the difference of $-0.08$ is within 1.7 standard errors from zero. The net operating assets slope is $-0.54$ in the subsample without bond ratings and $-0.52$ in the subsample with bond ratings: the difference of $-0.02$ is within 0.2 standard errors from zero.

We interpret the evidence as suggesting that the predictive power of investment-to-assets, asset growth, and investment growth for cross-sectional returns is likely driven by the negative expected return-investment relation implied by $q$-theory, but that the predictive power of net stock issues, abnormal corporate investment, and net operating assets is not. The evidence lends support to Cochrane (1991), Xing (2008), and Chen and Zhang (2009), but casts doubt on Lyandres, Sun, and Zhang (2008) and Wu, Zhang, and Zhang (2009). A caveat is that the abnormal corporate investment slope of $-0.06$ is within 1.9 standard errors from zero in the full sample. However, all the other investment variables have slopes that are at least five standard errors from zero.

Investment frictions provide an alternative interpretation to evidence commonly attributed to limits to arbitrage in prior studies.[2] Using our testing framework, we find that investment frictions and trading frictions are correlated: a firm whose stock is more costly to trade also faces more severe investment frictions. In particular, the correlations are $-0.61$ between asset size and idiosyncratic volatility, $-0.54$ between payout ratio and idiosyncratic volatility, and $-0.36$ between the bond rating dummy and trading volume. Investment frictions also reduce the impact of limits to arbitrage on the magnitude of the anomalies, more so for trading volume than for idiosyncratic volatility.

## 2 The Model

We build on the $q$-theory model of Cochrane (1991). There are two periods, 0 and 1, and heterogeneous firms, indexed by $i$. Firms use capital and costlessly adjustable inputs to produce a perishable good. The levels of these inputs are chosen each period to maximize the firms' operating profits, defined as revenues minus the expenditures on these inputs. Firm $i$'s operating profits are given by $\Pi K_{i0}$ in period 0 and $\Pi K_{i1}$ in period 1, in which $\Pi$ is the long-term average return on assets, which is time-invariant and constant across firms. Allowing $\Pi$ to vary over time and across firms does not change the basic insights. $K_{i0}$ and $K_{i1}$ are firm $i$'s capital in periods 0 and 1, respectively. The profit function exhibits constant returns to scale, meaning that $\Pi$ is both the marginal product of capital and the average product of capital. Taking the operating profits as given, firms choose optimal investment to maximize their market value.

Firm $i$ starts with capital stock, $K_{i0}$, invests in period 0, and produces in both periods. The firm exits at the end of period 1 with a liquidation value of $(1-\delta)K_{i1}$, in which $\delta$ is the rate of capital depreciation. Capital evolves as $K_{i1} = I_{i0} + (1-\delta)K_{i0}$, in which $I_{i0}$ is capital investment over period 0. When investing, firms incur general investment costs due to investment frictions. The general investment-cost function, denoted $C(I_{i0}, K_{i0})$, is increasing and convex in $I_{i0}$ and decreasing in $K_{i0}$. In particular, we assume that the investment-cost function is quadratic, that is,

$$C(I_{i0}, K_{i0}) = \frac{\lambda_i}{2}\left(\frac{I_{i0}}{K_{i0}}\right)^2 K_{i0} \tag{1}$$

We use the cost parameter $\lambda_i > 0$ to model the magnitude of the investment costs: firms with higher $\lambda_i$ face more investment frictions than firms with lower $\lambda_i$.

[2]Shleifer and Vishny (1997) argue that anomalies can persist if the costs of arbitrage outweigh the benefits of arbitrage aimed to exploit the anomalies. A sizable literature documents that anomalies are stronger in firms with more limits to arbitrage than in firms with less limits to arbitrage (e.g., Pontiff (1996), Ali, Hwang, and Trombley (2003), and Mashruwala, Rajgopal, and Shevlin (2006)).

Equation (1) does not restrict $I_{i0}$ to be positive. The total cost of investment is $I_{i0}+C(I_{i0}, K_{i0})$, in which $I_{i0}$ is the purchasing cost of the capital good when $I_{i0} \geq 0$ and is the resale value of the capital good when $I_{i0} < 0$ (negative cost). When $I_{i0} \geq 0$, the marginal (total) cost of investment is $1 + \partial C(I_{i0}, K_{i0})/\partial I_{i0} = 1 + \lambda_i(I_{i0}/K_{i0})$, which is greater than or equal to one. When $I_{i0} < 0$, the marginal (total) revenue of disinvestment continues to be $1 + \lambda_i(I_{i0}/K_{i0})$, which is less than one (the marginal resale value of the capital good) because of investment frictions.

Firm $i$ has a gross discount rate, denoted $R_i$. The discount rate varies across firms due to, for example, firm-specific loadings on macroeconomic risk factors. The firm chooses optimal investment, $I^*_{i0}$, to maximize its market value at the beginning of period 0:

$$\max_{\{I_{i0}\}} \quad \Pi K_{i0} - I_{i0} - \frac{\lambda_i}{2}\left(\frac{I_{i0}}{K_{i0}}\right)^2 K_{i0} + \frac{1}{R_i}\left[\Pi K_{i1} + (1-\delta)K_{i1}\right]. \tag{2}$$

The market value of firm $i$ is the sum of period 0's free cash flow, $\Pi K_{i0} - I_{i0} - (\lambda_i/2)\,(I_{i0}/K_{i0})^2\, K_{i0}$, and the discounted value of date 1's cash flow, $(\Pi K_{i1} + (1-\delta)K_{i1})\,/R_i$. In this two-period setup, firm $i$ does not invest in the second period, $I_{i1} = 0$, meaning that date 1's cash flow is the sum of the operating profits and the liquidation value of the capital.

The tradeoff of firm $i$ when making investment decisions is simple: foregoing free cash flows today in exchange for higher free cash flows tomorrow (when $I^*_{i0} \geq 0$), or increasing free cash flows today at the expense of lower free cash flows tomorrow (when $I^*_{i0} < 0$). Setting the first-order derivative of the objective function with respect to $I_{i0}$ to zero yields:

$$R_i = \frac{\Pi + 1 - \delta}{1 + \lambda_i(I^*_{i0}/K_{i0})}. \tag{3}$$

This optimality condition is intuitive. When $I^*_{i0} \geq 0$, the numerator in the right-hand side of equation (3) is the marginal benefit of investment, $\Pi + 1 - \delta$, including the marginal product of capital, $\Pi$, and the marginal liquidation value of capital, $1 - \delta$. The denominator is the marginal (total) cost of investment that includes the marginal purchasing cost of the capital good and the marginal investment cost. Because the marginal benefit of investment is in date 1's dollar terms and the marginal cost of investment is in date 0's dollar terms, the optimality condition says that the marginal benefit of investment, discounted in date 0's dollar terms, should be equal to the marginal cost of investment. Equivalently, the investment return (the ratio of the marginal benefit of investment in date 1's dollar terms divided by the marginal cost of investment in date 0's dollar terms) should equal the discount rate, as in Cochrane (1991).

The economic interpretation of equation (3) when $I^*_{i0} < 0$ is parallel. In particular, the numerator in the right-hand side of the equation is the foregone marginal benefit of investment in period 1, and the denominator is the period 0's marginal benefit of disinvestment that includes the marginal resale value of the capital good, net of the marginal disinvestment cost due to frictions. The optimality condition says that the foregone marginal benefit of investment in period 1, discounted in date 0's dollar terms, should equal the marginal benefit of disinvestment in period 0. Equivalently, the investment return should equal the discount rate, even when $I^*_{i0} < 0$.

Recognizing that $I^*_{i0}/K_{i0}$ is a function of $R_i$ and $\lambda_i$ (because of constant returns to scale, $I^*_{i0}/K_{i0}$ does not depend on $K_{i0}$), we totally differentiate equation (3) with respect to $R_i$ to obtain:

$$\frac{\partial(I^*_{i0}/K_{i0})}{\partial R_i} = -\frac{[1+\lambda_i(I^*_{i0}/K_{i0})]^2}{\lambda_i(\Pi+1-\delta)} < 0 \tag{4}$$

As such, investment and the discount rate are negatively correlated: investment predicts future returns with a negative slope, as in Cochrane (1991), Xing (2008), and Chen and Zhang (2009).

We are interested in knowing how $\lambda_i$ affects the investment-discount rate relation. To this end, we differentiate the absolute value of $\partial(I^*_{i0}/K_{i0})/\partial R_i$ with respect to $\lambda_i$ to obtain:

$$\partial\left|\frac{\partial(I^*_{i0}/K_{i0})}{\partial R_i}\right|/\partial\lambda_i = \frac{2[1+\lambda_i(I^*_{i0}/K_{i0})]}{\lambda_i(\pi+1-\delta)}\left[\frac{I^*_{i0}}{K_{i0}} + \lambda_i\frac{\partial(I^*_{i0}/K_{i0})}{\partial\lambda_i}\right] - \frac{[1+\lambda_i(I^*_{i0}/K_{i0})]^2}{\lambda_i^2(\pi+1-\delta)} \tag{5}$$

$$= -\frac{[1+\lambda_i(I^*_{i0}/K_{i0})]^2}{\lambda_i^2(\pi+1-\delta)} < 0, \tag{6}$$

in which the second equality follows because

$$\frac{I^*_{i0}}{K_{i0}} + \lambda_i\frac{\partial(I^*_{i0}/K_{i0})}{\partial\lambda_i} = 0. \tag{7}$$

This equation can be obtained from differentiating both sides of equation (3) with respect to $\lambda_i$.

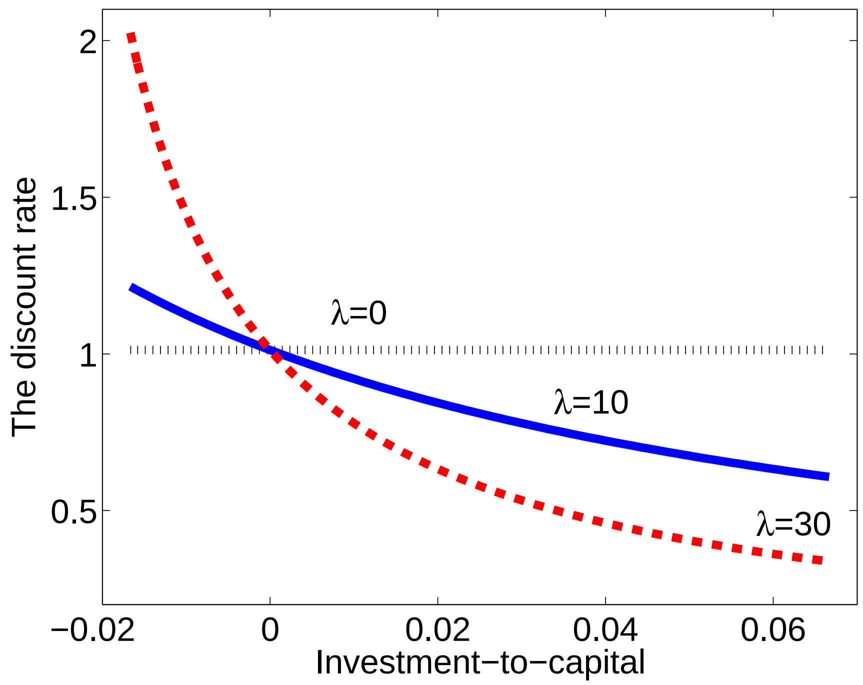
Figure 1 provides a graphical illustration of the economic mechanism at work. We let $I^*_{i0}/K_{i0}$ vary from $-20\%$ to $80\%$ per annum with $\delta = 0$ and $\Pi = 15\%$ per annum. We plot the monthly $R_i$ implied by equation (3) against monthly $I^*_{i0}/K_{i0}$ for three parameter values of $\lambda_i$: zero (no frictions, the black dotted line); ten (low frictions, the blue solid line), and 30 (high frictions, the red dashed line). As we gradually increase $\lambda_i$, the investment-discount rate relation, $\partial(I^*_{i0}/K_{i0})/\partial R_i$, becomes flatter, or equivalently, the discount rate-investment relation, $\partial R_i/\partial(I^*_{i0}/K_{i0})$ becomes steeper. In particular, when investment is frictionless, $\lambda_i = 0$, $I^*_{i0}/K_{i0}$ is vertical in the discount rate, or equivalently, the discount rate is flat in $I^*_{i0}/K_{i0}$.

**Figure 1 : The Discount Rate versus the Optimal Investment-to-Capital Ratio in the Simple $q$-theory Model**

We plot the discount rate, $R_i$, against the optimal investment-to-capital ratio, $I^*_{i0}/K_{i0}$, based on the functional form:

$$R_i = \frac{\Pi + 1 - \delta}{1 + \lambda_i (I^*_{i0}/K_{i0})}.$$

We plot the relation for three parameter values of $\lambda_i$: zero (no frictions, the black dotted line), ten (low frictions, the blue solid line), and 30 (high frictions, the red dashed line). We set $\pi = 0.15/12$ per month, $\delta = 0$, and let $I^*_{i0}/K_{i0}$ vary freely from $-0.20/12$ to $0.80/12$ per month.




The economic intuition is simple. The partial derivative, $\partial(I^*_{i0}/K_{i0})/\partial R_i$ measures the elasticity of optimal investment with respect to the discount rate. When investment is frictionless, $\lambda_i = 0$, investment is infinitely elastic to changes in the discount rate, meaning that $R_i$ is flat in $I^*_{i0}/K_{i0}$. With frictions, $\lambda_i > 0$, investment entails deadweight costs, and higher magnitude of investment-to-capital entails higher deadweight costs. As such, investment is no longer infinitely elastic to the discount rate. In addition, the magnitude of this elasticity decreases with $\lambda_i$. The higher $\lambda_i$ is, the more inelastic investment will be with respect to the discount rate. Equivalently, the higher $\lambda_i$ is, a given magnitude of change in investment-to-capital will correspond to a higher magnitude of change in the discount rate, meaning that investment-to-capital will be a more powerful predictor of future returns. In all, $q$-theory implies that investment is a more powerful predictor of future returns in firms with high investment frictions than in firms with low investment frictions. Our subsequent empirical analysis is centered around this central hypothesis.

# 3 Empirical Design

## 3.1 The Basic Idea

A natural test of the central hypothesis is to check how the magnitude of the expected return-investment relation varies across different subsamples of firms categorized by firm-level investment costs measures. As such, our primary test is to run firm-level Fama-MacBeth (1973) cross-sectional regressions of monthly percent excess returns on a given investment variable within each subsample. Under the $q$-theory logic, the magnitude of the slope on the anomaly variable should be higher in firms with high investment frictions than in firms with low investment frictions. To implement this idea, we need to identify firm-level proxies of investment frictions and to select investment-related variables. We tackle both issues in Section 3.2.

## 3.2 Data

We obtain accounting data from COMPUSTAT and stock returns data from the Center for Research in Security Prices (CRSP). All domestic common shares trading on NYSE, AMEX, and NASDAQ with accounting and returns data available are included except for financial firms (firms with four-digit SIC codes between 6000 and 6999). Following Fama and French (1993), we exclude closed-end funds, trusts, ADRs, REITS, and units of beneficial interest. We also exclude firms with negative book value of equity. To mitigate backfilling biases, we require firms to be listed on COMPUSTAT for two years before including them into our sample. We use the U.S. one-month Treasury bill rate from Kenneth French's Web site as the risk-free rate in computing excess returns. The sample contains in total 189,377 firm-year observations from 1963 to 2008.

### 3.2.1 Investment Frictions Measures

Our testable hypothesis is derived under a general formulation of the investment-cost function. We empirically identify investment frictions with firm-level measures of financing constraints. The basic idea is that if there are costs to investing, such as physical adjustment costs of capital, financing constraints increase these costs at the margin. The identification strategy also is simple to implement. In recent years the corporate finance literature has developed firm-level proxies for financing constraints that are reasonably well accepted (we provide detailed references later). In contrast, the literature that tests investment Euler equations (e.g., Whited (1992)) estimates the investment-cost parameter for a sample of firms, but does not provide firm-specific estimates.

We employ three measures of financing constraints: asset size, payout ratio, and bond ratings. Firms with small asset size, low payout ratios, or unrated corporate bonds are financially more constrained than firms with big asset size, high payout ratios, or rated corporate bonds.

*Asset Size.* We measure asset size as book value of total assets (COMPUSTAT annual item AT). At the end of June of each year $t$, we sort all firms into terciles based on total assets for the fiscal year ending in calendar year $t-1$ using NYSE, AMEX, and NASDAQ breakpoints. We assign those firms in the bottom tercile of the annual asset size distribution to the more constrained subsample and those firms in the top tercile to the less constrained subsample. Asset size is a standard measure of financing constraints (e.g., Gilchrist and Himmelberg (1995), Erickson and Whited (2000), Almeida and Campello (2007)): firms with small asset size are usually young, less well known, and are more affected by capital markets imperfections.

*Payout Ratio.* The payout ratio is the ratio of total distributions including dividends for preferred stocks (COMPUSTAT annual item DVP), dividends for common stocks (item DVC), and share repurchases (item PRSTKC) divided by operating income before depreciation (item OIBDP). At the end of June of each year $t$, we sort all firms into terciles based on their payout ratios for the fiscal year ending in calendar year $t-1$ using NYSE, AMEX, and NASDAQ breakpoints. We assign those firms in the bottom tercile of the annual payout ratio distribution to the more constrained subsample and those firms in the top tercile to the less constrained subsample. Similar to asset size, the payout ratio also is a traditional measure of financial constraints (e.g., Fazzari, Hubbard, and Peterson (1988), Almeida, Campello, and Weisbach (2004), and Almeida and Campello (2007)).

A complication arises when firms have negative earnings that makes the payout ratio ill-defined. There are in total 34,138 firm-year observations (18% of total observations) with negative earnings. Out of these observations, 10,299 (5.4% of total observations) have positive distributions (the sum of COMPUSTAT annual items DVP, DVC, and PRSTKC). The existing literature does not provide clear guidance on how to deal with firms with negative earnings. We use the following simple procedure. We assign firms with negative earnings but positive distributions to the less constrained subsample, and firms with negative earnings and zero distribution to the more constrained subsample.

*Bond Rating.* We retrieve data on firms' bond ratings from Standard & Poor's and categorize those firms that never had their public debt rated during our sample period as more constrained. Observations from those firms are only assigned to the constrained subsample in years when the firms report positive debt. The less constrained subsample contains those firms whose bonds have been rated during the sample period. This approach has been used extensively in the corporate finance literature (e.g., Kashyap, Lamont, and Stein (1994), Cummins, Hasset, and Oliner (1999), Almeida, Campello, and Weisbach (2004), and Almeida and Campello (2007)). We have experimented with commercial paper ratings as an alternative financing constraints measure as in Almeida et al., but the results are largely similar to those using bond ratings (not reported).[3]

#### 3.2.2 Anomaly Variables Related to Real Investment

We connect optimal investment-to-capital $q$-theory with a list of six variables that have been used to predict cross-sectional returns in prior studies.

*Investment-to-Assets, $I/A$.* Lyandres, Sun, and Zhang (2008) and Chen and Zhang (2009) use this variable as the primary investment variable motivated by $q$-theory. We measure $I/A$ as the change in gross property, plant, and equipment (COMPUSTAT annual item PPEGT) plus change in inventories (item INVT) divided by lagged total assets (item AT). Property, plant, and equipment represent long-lived assets for operations over many years such as buildings, machinery, furniture, and other equipment. Inventories represent short-lived assets within a normal operating cycle such as merchandise, raw materials, supplies, and work in progress. National Income Accounting also defines gross private domestic investment as the sum of fixed investment and the change in inventories.

*Asset Growth, $\triangle A/A$.* Cooper, Gulen, and Schill (2008) document that asset growth is a strong predictor of future abnormal returns, and interpret the evidence as suggesting that investors overextrapolate past growth too far into the future and that mispricing leads to potential investment policy distortions. Following their work, we measure asset growth as the change in total assets divided by lagged total assets (COMPUSTAT annual item AT). We view asset growth as the most comprehensive measure of investment-to-assets, in which investment is simply the change in total

[3] We have experimented with the Kaplan and Zingales (1997) index, but the index is weakly correlated with the other measures. Several recent studies cast doubt on this index as a valid measure of financing constraints (e.g., Almeida, Campello, and Weisbach (2004), Whited and Wu (2006), Hennessy and Whited (2007), and Hadlock and Pierce (2008)). Reestimating Kaplan and Zingales's ordered logit model on a larger, more recent sample, Hadlock and Pierce find that only two out of five components in the index have signs consistent with the original index. As such, we do not use the Kaplan-Zingales index. Whited and Wu (2006) propose another financing constraints index by combining cash flow-to-assets, a cash dividend dummy, long-term debt-to-assets, total assets, and industry and firm-level sales growth. The cross-sectional Spearman's correlation between asset size and their index is $-0.94$ in our sample. We opt to use asset size because it is simple and is unlikely to be affected by specification errors.

assets. Our tests can address whether $q$-theory plays a role in driving the asset growth effect.

*Investment Growth, $\triangle I/I$.* Xing (2008) documents that firms with low investment growth earns significantly higher returns on average than firms with high investment growth, and interprets the evidence as consistent with $q$-theory. Xing also shows that an investment growth factor, defined as the difference in returns between stocks with low investment growth and stocks with high investment growth, can account for the book-to-market effect roughly as well as Fama and French's (1993) value factor. We use Xing's definition of investment growth as the growth rate of capital expenditures (COMPUSTAT annual item CAPX). Including investment growth in our tests can address whether Xing's evidence is consistent with the $q$-theory interpretation.

*Net Stock Issues, $NSI$.* Combining evidence that returns following equity issues are low (e.g., Ritter (1991) and Loughran and Ritter (1995)) and that returns following stock repurchases are high (e.g., Ikenberry, Lakonishok, and Vermaelen (1995)), Daniel and Titman (2006), Fama and French (2008), and Pontiff and Woodgate (2008) show that net stock issues and average returns are negatively correlated. Li, Livdan, and Zhang (2008) argue that the net stock issues effect is connected to investment: the balance-sheet constraint of firms implies that the uses of funds must equal the sources of funds. Accordingly, Lyandres, Sun, and Zhang (2008) document that equity issuers invest more than nonissuers and that adding an investment factor into standard factor models substantially reduces the amount of long-term underperformance following equity issues.

We include $NSI$ into our tests to examine whether the net stock issues effect is consistent with the $q$-theory logic. Following Fama and French (2008), we measure net stock issues as the natural log of the ratio of the split-adjusted shares outstanding at the fiscal year ending in calendar $t-1$ divided by the split-adjusted shares outstanding at the fiscal year ending in $t-2$. We calculate the split-adjusted shares outstanding as COMPUSTAT shares outstanding (item CSHO) times COMPUSTAT adjustment factor (item ADJEX_C).

*Abnormal Corporate Investment, $ACI$.* Following Titman, Wei, and Xie (2004), we measure $ACI$ used for the portfolio formation year $t$ as $ACI_{t-1} = 3CE_{t-1}/(CE_{t-2} + CE_{t-3} + CE_{t-4}) - 1$, in which $CE_{t-1}$ is capital expenditures (COMPUSTAT annual item CAPX) divided by sales (item SALE) for the fiscal year ending in calendar year $t-1$. The prior three-year moving average of capital expenditures is designed to project the benchmark level of investment for the fiscal year $t-1$. An $ACI$ value greater than zero indicates that the past fiscal year's investment is greater than the average over the prior three years. In this sense, $ACI$ can be interpreted as a measure of abnormal investment. Titman et al. document that firms with high $ACI$ values earn significantly lower average returns than firms with low $ACI$ values. They interpret the evidence as investors underreacting to the empire building implications of increased investment expenditures. We use $ACI$ in our tests to see if the negative $ACI$-return relation can be interpreted using $q$-theory.

*Net Operating Assets, $NOA$.* Hirshleifer, Hou, Teoh, and Zhang (2004) document that the ratio of net operating assets scaled by lagged total assets is a strong negative predictor of cross-sectional returns. Net operating assets measure the cumulation over time of the difference between net operating income (accounting-value added) and free cash flow (cash-value added). Hirshleifer et al. argue that an accumulation of accounting earnings without a commensurate accumulation of free cash flows casts doubt on the sustainability of future profitability. In addition, investors have limited attention and fail to discount for this unsustainability. As such, high-$NOA$ firms are overvalued and should earn negative long-run abnormal returns, and low-$NOA$ firms are undervalued and should earn positive long-run abnormal returns.

We ask if $q$-theory plays a role in the negative $NOA$-return relation. Hirshleifer, Hou, Teoh, and Zhang (2004) show that the cumulative difference between operating income and free cash flow ($NOA$) equals the sum of the cumulative difference between operating income before depreciation and operating cash flow (cumulative operating accruals) and the cumulative investment. The latter results from fixed capital investing activities, while the former from working capital investing activities (e.g., Fairfield, Whisenant, and Yohn (2003)). Wu, Zhang, and Zhang (2009) show that controlling for investment-to-assets substantially reduces the predictive power of $NOA$ for future returns, and interpret the evidence as consistent with $q$-theory. We perform a more stringent test of $q$-theory by examining if the $NOA$ effect varies with investment costs.

We define $NOA$ as $OA - OL$ scaled by lagged total assets (COMPUSTAT annual item AT). $OA$ is operating assets: total assets minus cash and short-term investment (item CHE). $OL$ is operating liabilities: $TA - STD - LTD - MI - PS - CE$, in which $TA$ is total assets, $STD$ is debt included in current liabilities (item DLC), $LTD$ is long-term debt (item DLTT), $MI$ is minority interests (item MIB), $PS$ is preferred stocks (item PSTK), and $CE$ is common equity (item CEQ).

### 3.2.3 Descriptive Statistics

Table 1 reports descriptive statistics for the financing constraints measures and the investment-related variables. To alleviate the effect of outliers, we winsorize all variables at 1% and 99% before including them in our tests. From Panel A, the asset size distribution is highly skewed toward small firms: the median asset size is 75.41 million dollars but the mean asset size is more than ten times larger at 839.83 million dollars. The payout ratio has a mean of 0.13, a median of 0.03, and a standard deviation of 0.27. (In calculating these descriptive statistics, we do not include firm-year observations with negative earnings but positive distributions. As noted, we treat these observations as less constrained.) We define the bond rating dummy to take the value of one when firms report positive but unrated debt. From Panel A, on average, 53% of firms belong to the more constrained group per the bond rating criterion.

The financing constraints measures are correlated. We calculate pairwise cross-sectional Spearman's rank correlations for each year and report time series averaged correlations. From Panel B, the correlations are 0.51 between asset size and payout ratio, $-0.37$ between asset size and bond rating dummy, and $-0.21$ between payout ratio and bond rating dummy. Evaluated with time series standard errors, all the correlations are significant at the 1% level. The evidence suggests that, intuitively, small asset firms are more likely to have low payout ratios and unrated public debt issues than big asset firms. In addition, firms with low payout ratios are more likely to have unrated public debt than firms with high payout ratios.

Turning to the investment measures, Panel A shows that the average investment-to-assets, $I/A$, is 4% per annum. Even after winsorization at 1% and 99%, $I/A$ has a standard deviation of 23% and varies from $-0.47$ to 2.20. Asset growth, $\triangle A/A$, has a mean of 11% per annum and a standard deviation of 46%. The distribution of investment growth is skewed: its mean is 30%, but the median is only $-2$%. The mean of net stock issues is 2% per annum, while the median is zero. The mean of abnormal corporate investment, $ACI$, is $-22$% and the median is $-36$%. Because $ACI$ is the growth rate of investment-to-sales relative to its prior three-year average, this evidence suggests strong mean reversion in the investment-to-sales ratio. Finally, the distribution of net operating assets is symmetric: its mean is 0.63, which is close to the median of 0.68.

Panel B shows that the six investment measures are positively correlated. The pairwise Spearman correlations vary from 0.17 to 0.74 and are all significant at the 1% level. In particular, as our primary investment measure, investment-to-assets is highly correlated with the other measures: 0.74 with asset growth, 0.59 with investment growth, 0.44 with net stock issues, 0.32 with abnormal corporate investment, and 0.60 with net operating assets. The net stock issues variable has a low correlation of 0.17 with abnormal corporate investment but high correlations of 0.54, 0.36, and 0.43

with asset growth, investment growth, and net operating assets, respectively. Abnormal corporate investment has a low correlation of 0.26 with net operating assets and with asset growth, but a high correlation of 0.52 with investment growth.

# 4 Empirical Results

## 4.1 Testing the Slope Prediction

For each month from July of year $t$ to June of year $t+1$, we run Fama-MacBeth (1973) cross-sectional regressions of monthly percent excess returns on a given investment variable for the fiscal year ending in the calendar year $t-1$. We run the regressions in the full sample as well as in extreme subsamples split by a given financing constraints proxy, and compare the slopes on a given investment variable across the extreme subsamples. We split the sample in June of each year $t$ based on a given constraints proxy for the fiscal year ending in calendar year $t-1$. The sample is from July 1963 to December 2008. Under the $q$-theory logic, the magnitude of the slopes should be higher in the more constrained subsample than in the less constrained subsample.

### 4.1.1 Benchmark Estimation

Table 2 reports the details. The first two rows of the table show that all six investment variables predict returns negatively in the full sample. All variables except for abnormal corporate investment, $ACI$, have slopes that are significant at the 1% level. In particular, investment-to-assets has a slope of $-0.74$ that is more than five standard errors from zero, and asset growth has a slope of $-0.78$ that is more than eight standard errors from zero. Relative to the other variables, $ACI$'s predictive power is substantially weaker: its slope is $-0.06$, which is within 1.9 standard errors from zero.

Turning to our key tests, Table 2 shows that the slopes of investment-to-assets, asset growth, and investment growth are significantly higher in magnitude in the more constrained subsample than in the less constrained subsample. From Panel A, the slope of $I/A$ is $-1.05$ in the subsample of small asset size and is $-0.34$ in the subsample of big asset size. The difference of $-0.71$ is more than 2.9 standard errors from zero. (The standard error is the time series standard error of the slope difference between the two subsamples.) Using the payout ratio as the financing constraints proxy yields largely similar results: the $I/A$ slope is $-1.02$ in the low payout subsample and $-0.34$ in the high payout subsample. The difference of $-0.68$ is more than three standard errors from zero. Finally, the $I/A$ slope is $-0.93$ in the subsample without bond ratings and $-0.51$ in the subsample with bond ratings: the difference of $-0.42$ is more than 2.6 standard errors from zero.

The asset growth results are similar to those for investment-to-assets. Panel B shows that the $\triangle A/A$ slope is $-0.93$ in the small asset subsample and $-0.50$ in the big asset subsample: the difference of $-0.43$ is more than 2.7 standard errors from zero. Using payout ratio again yields similar results as asset size. When we use bond rating dummy to measure investment frictions, the $\triangle A/A$ slope is $-0.93$ in the subsample without bond ratings and $-0.56$ in the subsample with bond ratings: the difference is more than 3.4 standard errors from zero.

Although going in the same direction, the investment growth results are weaker than those for investment-to-asset and asset growth. In particular, Panel C shows that the difference in the $\triangle I/I$ slope is only $-0.03$ across the small and big asset size subsamples, and is within 0.9 standard errors from zero. The slope difference is $-0.06$ across the low and high payout ratio terciles, and is slightly more than two standard errors from zero. Finally, the slope difference is at the same level of $-0.06$ across the subsamples with and without bond ratings. However, the difference is more precisely estimated, and is more than 2.5 standard errors from zero.

The remaining panels show that the slopes of net stock issues, abnormal corporate investment, and net operating assets are not significantly different across extreme financing constraints subsamples. From Panel D, the slope of net stock issues ($NSI$) is $-1.63$ in the small asset subsample, and $-1.54$ in the big asset subsample: the difference is within 0.3 standard errors from zero. Similarly, the $NSI$ slope is $-2.03$ in the subsample without bond ratings and $-1.84$ in the subsample with bond ratings: the difference is within 0.6 standard errors from zero. The $NSI$ slope is even higher in magnitude in the less constrained firms than in the more constrained firms as defined by the payout ratio: $-1.77$ versus $-1.60$, but the difference is within 0.5 standard errors from zero.

From Panel E, the slope of abnormal corporate investment ($ACI$) is $-0.05$ in the small asset subsample and 0.03 in the big asset subsample. However, the difference of $-0.08$ is within 1.5 standard errors from zero. The difference in the $ACI$ slope between the low and high payout ratio subsamples also stands at $-0.08$, which is within 1.7 standard errors from zero. The evidence with bond ratings goes in the opposite direction as predicted by $q$-theory. The $ACI$ slope is $-0.04$ in the more constrained subsample, but is $-0.10$ in the less constrained subsample, although the difference is within 1.6 standard errors from zero. Finally, Panel F shows that although the net operating assets ($NOA$) effect is stronger in more constrained firms than in less constrained firms, the difference is insignificant. In particular, the $NOA$ slope is $-0.52$ in the small asset subsample and $-0.42$ in the big asset subsample, and the difference is within 0.8 standard errors from zero.

#### 4.1.2 Alternative Specifications

We report two robustness checks on our key results in Table 2. First, we examine the impact of the January effect, which means a general increase in stock prices in January. This effect is often attributed to buying activities that follow the drop in prices in December when investors sell to create tax losses and offset capital gains. Keim (1983) shows that much of the abnormal returns to small firms occurs in January. However, we are not aware of any prior attempt to examine whether the investment-related effects are driven by the January effect.

In Panel A of Table 3 we rerun the tests from Table 2 but without the January returns. The first two rows of the panel show that the abnormal corporate investment effect of Titman, Wei, and Xie (2004) is driven entirely by the January returns. Without them the $ACI$ slope is close to zero in cross-sectional regressions. The slopes for the other investment variables are somewhat reduced in magnitude, but all the slopes remain at least 3.9 standard errors from zero. In particular, the $I/A$ slope reduces from $-0.74$ to $-0.57$, which is still about four standard errors from zero. The $NSI$ slope even increases slightly from $-1.96$ to $-2.12$, which is almost eight standard errors from zero.

The investment-to-assets slope is higher in magnitude in more constrained subsamples without January returns. In particular, the $I/A$ slope is $-0.81$ in the small asset subsample and $-0.29$ in the big asset subsample: the difference of $-0.52$ is more than 2.1 standard errors from zero. The difference of $-0.36$ in the $I/A$ slope between the extreme payout ratio subsamples is insignificant ($t = -1.6$). But the difference of $-0.48$ between subsamples without and with bond ratings is more than 3.1 standard errors from zero. The magnitude of the $\triangle A/A$ slope also is higher in more constrained firms than in less constrained firms: $-0.77$ versus $-0.40$ across small and big asset subsamples, $-0.69$ versus $-0.44$ across low and high payout ratio subsamples, and $-0.77$ versus $-0.40$ across firms without and with bond ratings. The slope differences are significant in all three cases.

Dropping January returns weakens the differences in the investment growth slope across extreme financing constraints subsamples to insignificant levels. The $\triangle I/I$ slope differs across firms with and without bond ratings by $-0.04$, although it is marginally significant. The slope differences are even smaller in magnitude across extreme asset size and payout ratio subsamples, and are both within 0.8 standard errors from zero. As in the benchmark estimation, the $NSI, ACI$, and $NOA$

slopes do not differ significantly across extreme financing constraints subsamples.

In the second robustness test, we ask how the results change after we control for the standard determinants of cross-sectional returns such as the market capitalization, book-to-market equity, and prior six-month returns. A caveat is that these controls are linked to investment: small firms, growth firms, and winners with high prior six-month returns tend to invest more than big firms, value firms, and losers with low prior six-month returns, respectively. These correlations can make the interpretation of any individual slope in multiple regressions less straightforward than in the slope in univariate regressions. However, it remains informative to check to what extent our inferences are robust to the inclusion of these standard controls.

Panel B of Table 3 reports the details. Including the standard controls reduces the $ACI$ effect to insignificance: its regression slope of $-0.03$ is within 1.3 standard errors from zero. The five other investment variables retain strong predictive power for cross-sectional returns: all the slopes are at least 4.5 standard errors away from zero. The $I/A$ and $\triangle A/A$ slopes are somewhat reduced in magnitude relative to the benchmark estimates, but the other slopes are largely similar.

The magnitude of the $I/A$ slope continues to be significantly higher in more constrained firms than in less constrained firms: the difference is $-0.63$ across small and big asset size subsamples ($t = -2.8$), $-0.48$ across low and high payout ratio subsamples ($t = -2.5$), and $-0.40$ across firms without and with bond ratings ($t = -2.7$). However, although the $\triangle A/A$ slope is significantly different across subsamples split by bond ratings, the differences across asset size and payout ratio subsamples are within 1.9 standard errors from zero. Relative to the benchmark estimates, the $\triangle I/I$ results are substantially weakened: all the slope differences across extreme financing constraints subsamples are within 1.4 standard errors from zero. As in the benchmark specification, the $NSI$ and $ACI$ effects do not vary much with financing constraints. Unlike the benchmark specification, the $NOA$ slope differs significantly across extreme subsamples using two out of three financing constraints proxies.

## 4.2 Implications for Limits to Arbitrage

Many empirical studies interpret the asset growth, net stock issues, abnormal corporate investment, and net operating assets anomalies as driven by systematic mispricing.[4] If these anomalies are due

[4]See, for example, Ritter (1991), Ikenberry, Lakonishok, and Vermaelen (1995), Loughran and Ritter (1995), Hirshleifer, Hou, Teoh, and Zhang (2004), Titman, Wei, and Xie (2004), and Cooper, Gulen, and Schill (2008). In particular, Hirshleifer et al. interpret the net operating assets effect as investors with limited information overvaluing firms in which cumulative net income over time outstrips cumulative free cash flow and undervaluing firms in which cumulative net income falls short of cumulative free cash flow. Titman et al. interpret the abnormal investment-return

to mispricing, why do professional arbitrageurs not exploit the trading opportunities to eliminate the mispricing? Shleifer and Vishny (1997) argue that because of trading frictions, arbitrage can be costly and limited. When the costs of arbitrage outweigh the benefits of arbitrage, mispricing might not be quickly and entirely traded away. While our story stresses the importance of investment frictions from the firms' side, the limits to arbitrage story stresses the importance of trading frictions from the investors' side. Because the two stories ride on different types of frictions that probably coexist in the data, they are not mutually exclusive. More important, if trading frictions and investment frictions are positively correlated (a company whose stock is more costly to trade might also face high investment costs), it is possible that $q$-theory provides an alternative interpretation to evidence that has been attributed to limits to arbitrage in prior literature.

We investigate this possibility within our testing framework. We take a couple of standard limits to arbitrage proxies. After showing that these proxies are correlated with investment frictions measures, we ask how much investment frictions can explain the effect of limits to arbitrage on the magnitude of the anomalies. Conversely, we ask to what extent the investment frictions effect can subsist after controlling for measures of limits to arbitrage.

#### 4.2.1 Proxies for Limits to Arbitrage

We employ two standard proxies for limits to arbitrage, idiosyncratic stock volatility and dollar trading volume (e.g., Ali, Hwang, and Trombley (2003)). The idea behind idiosyncratic volatility is that arbitrage strategies are not diversified, meaning that arbitrageurs must take idiosyncratic volatility without being compensated with higher expected returns. As such, high idiosyncratic volatility implies that arbitrage is more costly and limited, and low idiosyncratic volatility implies that arbitrage is less costly and limited. The idea behind dollar trading volume is transaction costs. When stocks are mispriced, transaction costs limit the extent to which arbitrageurs can exploit the trading opportunities to eliminate the mispricing. Dollar volume is an indicator of transaction costs in the form of adverse price effects of a trade and the delay in processing the trade. If stocks are heavily traded, trades are more likely to be completed quickly and are less likely to have adverse price impact. If stocks are thinly traded, trades are less likely to be completed quickly and are more likely to have adverse price impact. Arbitrages are more limited for stocks with low trading volume.

relation as consistent with the hypothesis that "investors tend to underreact to the empire building implications of increased investment expenditures (p. 677)." Cooper et al. argue that the asset growth effect means that "bias in the capitalization of new investments leads to a host of potential investment policy distortions" and that "such potential distortions are present and economically meaningful (p. 1648)."

We regress daily stock returns on a value-weighted market portfolio over a maximum of 250 days ending on June 30 of year $t$ and calculate idiosyncratic volatility as the standard deviation of the residuals. Dollar trading volume is the annual volume of trade in a firm's shares from July 1 of year $t-1$ to June 30 of year $t$, in millions of dollars. At the end of each June, we compute dollar volume for each firm as the sum of last twelve months' daily dollar volume, which is the product of share volume and daily closing price from CRSP.

The limits to arbitrage proxies are correlated with financial constraints measures. In June of each year $t$ we calculate the pairwise cross-sectional Spearman's correlations between limits to arbitrage proxies at the end of June of year $t$ and financing constraints measures for the fiscal year ending in calendar year $t-1$. We then compute average correlations in the time series. Small asset firms have high idiosyncratic volatility and low dollar trading volume: the correlations are $-0.61$ between asset size and idiosyncratic volatility and 0.73 between asset size and trading volume. Low payout firms have high idiosyncratic volatility and low trading volume: the correlations are $-0.54$ between payout ratio and idiosyncratic volatility and 0.32 between payout ratio and trading volume. Firms without bond ratings have high idiosyncratic volatility and low trading volume: the correlations are 0.29 between the bond rating dummy and idiosyncratic volatility and $-0.36$ between the bond rating dummy and trading volume. All these correlations are significant at the 1% level when evaluated with time series standard errors.

These correlations make sense. Asset size, which is a standard financing constraints measure, can indicate trading frictions. Firms with small asset size are more likely to be thinly traded with lower liquidity and higher transactions costs than firms with big asset size. Small asset firms also are more likely to be poorly diversified in their operating, investing, and financing activities and have higher idiosyncratic volatilities than big asset firms. Firms with high trading volume are more likely to have easy access to equity markets and low equity financing costs than firms with low trading volume. In addition, to the extent that idiosyncratic volatility affects a firm's default probability à la Merton (1974), firms with high idiosyncratic volatility are more likely to have high default probability and high costs of debt financing than firms with low idiosyncratic volatility. These economic links suggest that the effect of limits to arbitrage on the anomalies documented in the prior literature might in part be driven by investment frictions.

### 4.2.2 Trading Frictions versus Investment Frictions

To test this possibility, we first document the effect of limits to arbitrage. In June of each year $t$ we halve the sample based on the medium idiosyncratic volatility and, independently, on the medium dollar trading volume. Unlike financing constraints measures that are only available at the last fiscal year end, we use information up to the end of June of year $t$ to calculate these two measures. Within each subsample, we run cross-sectional regressions of monthly percent excess returns from July of year $t$ to June of year $t+1$ on a given investment variable for the fiscal year ending in calendar year $t-1$. We test whether the slope of the investment variable is equal across the subsamples split by a given limits to arbitrage proxy.

From the first two rows of Table 4, the investment-to-assets, asset growth, and net operating assets effects are significantly stronger in the high idiosyncratic volatility subsample and in the low trading volume subsample. In particular, the difference in the investment-to-assets slope is $-0.74$ ($t = -3.9$) across the volatility subsamples, and is $-0.58$ ($t = -2.9$) across the volume subsamples. The difference in the asset growth slope is $-0.57$ ($t = -4.7$) across the volatility subsamples, and is $-0.34$ ($t = -2.2$) across the volume subsamples. The difference in the investment growth slope is significant across the volatility subsamples, but is not across the volume subsamples. The difference in the $ACI$ slope is marginally significant across the volume subsamples, but is not across the volatility subsamples. Finally, the difference in the $NSI$ slope is insignificant across the volatility subsamples and across the volume subsamples. The evidence suggests that limits to arbitrage are likely important for the investment-to-assets, asset growth, and net operating assets effects, but are not for the investment growth, abnormal investment, and net stock issues effects.

We are interested in knowing how much the effect of trading frictions on the magnitude of the anomalies can be explained by investment frictions. To this end we split the sample jointly by a trading frictions measure and an investment frictions measure. In June of each year $t$, we sort firms into two groups based on the medium of a given trading frictions measure. We also independently sort firms into two groups around the medium of a given financing constraints measure for the fiscal year ending in calendar year $t-1$. Taking interactions partitions the full sample into four subsamples. (Using the two-by-two sort instead of a three-by-three sort ensures that there are enough firms in a given subsample.) We run cross-sectional regressions of monthly percent excess returns from July of year $t$ to June of $t+1$ on a given investment variable for the fiscal year ending in calendar year $t-1$ in each subsample. We calculate the slope differences and their $t$-statistics across subsamples along a given measure of trading frictions or investment frictions.

Rows three to 14 in Table 4 show that investment frictions reduce the effect of trading frictions. If investment frictions do not add any relevant information, the slope difference across subsamples split by trading frictions should not be affected by controlling for investment frictions. The evidence says otherwise. The $I/A$ slope difference across the high and the low idiosyncratic volatility subsamples decreases in magnitude from $-0.74$ in the full sample to $-0.58$ in the small-asset universe and to $-0.48$ in the big-asset universe. The corresponding $t$-statistic decreases from $-3.9$ in the full sample to $-2.4$ in the small asset universe and to $-2.0$ in the big asset universe. The $\triangle A/A$ slope difference across the high and the low idiosyncratic volatility subsamples decreases in magnitude from $-0.57$ ($t = -4.7$) in the full sample to $-0.42$ ($t = -3.0$) in the low-payout universe and to $-0.41$($t = -2.4$) in the high-payout universe.

Investment frictions are more effective in reducing the effect of trading volume. The $I/A$ slope difference across the high and the low trading volume subsamples decreases in magnitude from $-0.58$ ($t = -2.9$) in the full sample to $-0.47$ in the small-asset universe and to 0.12 in the big-asset universe. Both are within 1.3 standard errors from zero. The $\triangle A/A$ slope difference across the high and the low trading volume subsamples decreases in magnitude from $-0.34$ ($t = -2.2$) in the full sample to $-0.10$ in the small-asset universe and to $-0.13$ in the big-asset universe. Both are within 0.7 standard errors from zero. Asset size also is effective in reducing the $NOA$ slope difference across trading volume subsamples. The results of the bond rating dummy are largely similar to those of asset size, but the payout ratio is less effective in reducing the effect of trading volume.

The remaining 12 rows in Table 4 document the effect of investment frictions after controlling for trading frictions. The evidence suggests that the effect of investment frictions is similar to the effect of dollar volume but is weaker than the effect of idiosyncratic volatility. The $I/A$ slope difference is only significant across the low and high payout subsamples in the low idiosyncratic volatility universe, $-0.46$ ($t = -2.33$). Although all going in the right direction, the $I/A$ slope differences are insignificant in all the other cases. Similarly, the $\triangle A/A$ slope difference is significant, $-0.29$ ($t = -2.1$), across the subsamples with and without bond ratings in the high idiosyncratic volatility universe, but is insignificant in all the other cases. In contrast, the slope differences are significant more often when we control for trading volume. The $I/A$ slope difference across the subsamples with and without bond ratings is $-0.62$ ($t = -2.2$) in the low volume universe and is $-0.39$ ($t = -1.8$) in the high volume universe. The results are largely similar for the $\triangle A/A$ slope difference.

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**Table 1 : Descriptive Statistics (July 1963–December 2008)**

This table reports descriptive statistics for financing constraints measures and investment measures. Asset size (in millions of dollars) is book value of total assets (COMPUSTAT annual item AT). The payout ratio is the ratio of total distributions including dividends for preferred stocks (item DVP), dividends for common stocks (item DVC), and share repurchases (item PRSTKC) divided by operating income before depreciation (item OIBDP). We do not calculate the payout ratios for firms with negative earnings but positive distributions. We retrieve data on firms' bond ratings from Standard & Poor's and categorize those firms that never had their public debt rated during our sample period as financially constrained (rating dummy = 1). Observations from those firms are only assigned to the constrained subsample in years when the firms report positive debt. The financially unconstrained subsample contains those firms whose bonds have been rated during the sample period (rating dummy = 0). Investment-to-assets ($I/A$) is the annual change in gross property, plant, and equipment (COMPUSTAT annual item PPEGT) plus the annual change in inventories (item INVT) divided by the lagged book value of assets (item AT). Asset growth ($\triangle A/A$) is the change in total assets (item AT) divided by lagged total assets. Investment growth ($\triangle I/I$) is the growth rate of capital expenditure (item CAPX). Net stock issues ($NSI$) are the natural log of the ratio of the split-adjusted shares outstanding at the fiscal year-end in $t$–1 divided by the split-adjusted shares outstanding at the fiscal year-end in $t$–2. The split-adjusted shares outstanding is COMPUSTAT shares outstanding (item CSHO) times the COMPUSTAT adjustment factor (item AJEX). Abnormal corporate investment ($ACI$) is $3CE_{t-1}/(CE_{t-2}+CE_{t-3}+CE_{t-4})-1$, in which $CE_{t-1}$ is capital expenditures (item CAPX) scaled by its sales (item SALE) for the fiscal year ending in calendar year $t-1$. Net operating assets ($NOA$) are operating assets minus operating liabilities, in which operating assets are calculated as total assets (item AT) minus cash and short-term investment (item CHE). Operating liabilities are total assets minus debt included in current liabilities (item DLC) minus long-term debt (item DLTT) minus minority interests (item MIB) minus preferred stocks (item PSTK) minus common equity (item CEQ). We winsorize all variables at 1% and 99%. In Panel A we calculate the statistics by pooling all the time series and cross-sectional observations. In Panel B we calculate the pairwise cross-sectional Spearman's rank correlations for each year and report time series averaged correlations. The significance of a given correlation (calculated with time series standard errors) is indicated with a star system: one and two stars denote 5% and 1% significance levels, respectively.

Panel A: Descriptive statistics

| | Mean | Std | Min | 25% | Median | 75% | Max |
|---|---|---|---|---|---|---|---|
| Asset size | 839.83 | 3032.84 | 1.06 | 18.87 | 75.41 | 360.51 | 48350.70 |
| Payout ratio | 0.13 | 0.27 | 0.00 | 0.00 | 0.03 | 0.17 | 3.70 |
| Rating dummy | 0.53 | 0.50 | 0.00 | 0.00 | 1.00 | 1.00 | 1.00 |
| $I/A$ | 0.04 | 0.23 | −0.47 | −0.02 | 0.05 | 0.13 | 2.20 |
| $\triangle A/A$ | 0.11 | 0.46 | −0.65 | −0.06 | 0.06 | 0.19 | 7.32 |
| $\triangle I/I$ | 0.30 | 1.69 | −0.99 | −0.52 | −0.02 | 0.48 | 18.54 |
| $NSI$ | 0.02 | 0.14 | −0.22 | 0.00 | 0.00 | 0.02 | 1.19 |
| $ACI$ | −0.22 | 0.87 | −0.99 | −0.90 | −0.36 | 0.08 | 6.50 |
| $NOA$ | 0.63 | 0.39 | −0.34 | 0.43 | 0.68 | 0.83 | 4.20 |

Panel B: Cross correlations (Spearman)

| | Asset size | Payout ratio | Bond rating | $I/A$ | $\triangle A/A$ | $\triangle I/I$ | $NSI$ | $ACI$ | $NCO$ |
|---|---|---|---|---|---|---|---|---|---|
| Asset size | 1 | | | | | | | | |
| Payout ratio | 0.51** | 1 | | | | | | | |
| Rating dummy | −0.37** | −0.21** | 1 | | | | | | |
| $I/A$ | 0.22** | 0.08** | 0.01 | 1 | | | | | |
| $\triangle A/A$ | 0.27** | 0.11** | −0.04** | 0.74** | 1 | | | | |
| $\triangle I/I$ | 0.20** | 0.12** | 0.00 | 0.59** | 0.52** | 1 | | | |
| $NSI$ | 0.20** | −0.06 | −0.03** | 0.44** | 0.54** | 0.36** | 1 | | |
| $ACI$ | 0.31** | 0.26** | −0.07** | 0.32** | 0.26** | 0.52** | 0.17** | 1 | |
| $NOA$ | 0.32** | 0.17** | 0.02* | 0.60** | 0.65** | 0.39** | 0.43** | 0.26** | 1 |

**Table 2 : Slopes from Fama-MacBeth (1973) Cross-Sectional Regressions of Monthly Percent Excess Returns on Anomaly Variables in the Full Sample and Subsamples Split by Financing Constraints Measures (July 1963–December 2008, 558 Months)**

For each month from July of year $t$ to June of year $t+1$, we run Fama-MacBeth cross-sectional regressions of monthly percent excess returns on a given anomaly variable for the fiscal year ending in calendar year $t-1$ in the full sample as well as in extreme subsamples split by a given financing constraints measure. For firms with negative earnings but positive payouts, we do not calculate their payout ratios but categorize them as financially least constrained (along with firms with high payout ratios). We report the slopes and their Fama-MacBeth $t$-statistics (in parentheses). We also report the $t$-statistics (in brackets) testing that a given slope is equal across extreme subsamples split by a given financing constraints measure. Excess returns are the difference between portfolio returns and one-month Treasury bill rate (from Kenneth French's Web site). $I/A$ is investment-to-assets, $\triangle A/A$ is asset growth, $\triangle I/I$ is investment growth, $NSI$ is net stock issues, $ACI$ is abnormal corporate investment, and $NOA$ is net operating assets. See the caption of Table 1 for detailed variable definitions.

| | Panel A: $I/A$ | Panel B: $\triangle A/A$ | Panel C: $\triangle I/I$ | Panel D: $NSI$ | Panel E: $ACI$ | Panel F: $NOA$ |
|---|---|---|---|---|---|---|
| Full Sample | −0.74 | −0.78 | −0.09 | −1.96 | −0.06 | −0.54 |
| | (−5.2) | (−8.4) | (−5.8) | (−7.2) | (−1.9) | (−5.3) |
| Small asset size | −1.05 | −0.93 | −0.09 | −1.63 | −0.05 | −0.52 |
| | (−6.3) | (−8.3) | (−5.4) | (−4.8) | (−1.3) | (−4.1) |
| Big asset size | −0.34 | −0.50 | −0.06 | −1.54 | 0.03 | −0.42 |
| | (−1.8) | (−3.9) | (−1.7) | (−4.9) | (0.8) | (−4.8) |
| Small-minus-big | [−2.9] | [−2.8] | [−0.9] | [−0.2] | [−1.5] | [−0.7] |
| Low payout ratio | −1.02 | −0.89 | −0.10 | −1.60 | −0.10 | −0.54 |
| | (−6.1) | (−8.1) | (−5.1) | (−5.0) | (−2.6) | (−4.9) |
| High payout ratio | −0.34 | −0.54 | −0.04 | −1.77 | −0.02 | −0.47 |
| | (−1.9) | (−4.6) | (−1.9) | (−5.5) | (−0.8) | (−4.8) |
| Low-minus-high | [−3.1] | [−2.7] | [−2.0] | [0.4] | [−1.6] | [−0.6] |
| With bond rating | −0.51 | −0.56 | −0.05 | −1.84 | −0.10 | −0.52 |
| | (−2.8) | (−4.8) | (−2.4) | (−5.8) | (−2.6) | (−4.3) |
| Without bond rating | −0.93 | −0.93 | −0.11 | −2.03 | −0.04 | −0.54 |
| | (−6.5) | (−9.4) | (−6.5) | (−6.5) | (−1.2) | (−5.3) |
| Without-minus-with | [−2.7] | [−3.4] | [−2.5] | [−0.6] | [1.6] | [−0.2] |

**Table 3 : Slopes from Fama-MacBeth (1973) Cross-Sectional Regressions of Monthly Percent Excess Returns on Anomaly Variables in the Full Sample and Subsamples Split by Financing Constraints Measures, Robustness Checks**

In Panel A, for each month from July of year $t$ to June of year $t+1$ (except for January of year $t+1$) we run cross-sectional regressions of monthly percent excess returns on a given anomaly variable for the fiscal year ending in calendar year $t-1$ in the full sample as well as in extreme subsamples split by a given financing constraints measure. In Panel B the regressions are run with January returns as well as three controls: the log market capitalization at the end of June of year $t$, the log book-to-market equity as the log book equity for the fiscal year ending in $t-1$ minus the log market equity at the end of December of year $t-1$, and the log prior six-month returns (with one-month gap between the holding period and the current month). We report the slopes and their Fama-MacBeth $t$-statistics (in parentheses), as well as the $t$-statistics (in brackets) testing that a given slope is equal across extreme subsamples split by a given financing constraints measure. For firms with negative earnings but positive payouts, we do not calculate their payout ratios but categorize them as financially least constrained (along with firms with high payout ratios). Excess returns are the difference between portfolio returns and one-month Treasury bill rate (from Kenneth French's Web site). $I/A$ is investment-to-assets, $\triangle A/A$ is asset growth, $\triangle I/I$ is investment growth, $NSI$ is net stock issues, $ACI$ is abnormal corporate investment, and $NOA$ is net operating assets. See the caption of Table 1 for detailed variable definitions. Book equity is the COMPUSTAT book value of stockholders' equity (COMPUSTAT annual item SEQ), plus balance sheet deferred taxes (item TXDB) and investment tax credit (item ITCI, if available), minus the book value of preferred stock. Depending on availability, we use redemption (item PSTKRV), liquidation (item PSTKL), or par value (item PSTK, in that order) to estimate the book value of preferred stock. Market equity is CRSP price per share times the number of shares outstanding (SHROUT).

| | Panel A: No January returns (July 1963–December 2008, 513 Months) | | | | | | Panel B: Controlling for size, book-to-market, and prior returns (July 1963–December 2008, 558 Months) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $I/A$ | $\triangle A/A$ | $\triangle I/I$ | $NSI$ | $ACI$ | $NOA$ | $I/A$ | $\triangle A/A$ | $\triangle I/I$ | $NSI$ | $ACI$ | $NOA$ |
| Full Sample | −0.57 | −0.62 | −0.09 | −2.12 | −0.00 | −0.40 | −0.56 | −0.57 | −0.07 | −1.38 | −0.03 | −0.56 |
| | (−4.0) | (−6.9) | (−6.5) | (−8.0) | (−0.1) | (−3.9) | (−4.6) | (−7.4) | (−5.9) | (−6.3) | (−1.2) | (−7.2) |
| Small asset size | −0.81 | −0.77 | −0.08 | −2.05 | −0.03 | −0.44 | −0.84 | −0.65 | −0.07 | −1.23 | −0.07 | −0.74 |
| | (−5.1) | (−7.1) | (−4.9) | (−6.3) | (−0.7) | (−3.4) | (−5.3) | (−6.4) | (−4.5) | (−3.9) | (−1.9) | (−6.1) |
| Big asset size | −0.29 | −0.40 | −0.06 | −1.65 | 0.07 | −0.39 | −0.21 | −0.38 | −0.05 | −1.35 | 0.04 | −0.41 |
| | (−1.4) | (−3.1) | (−1.8) | (−5.2) | (1.7) | (−4.3) | (−1.2) | (−3.5) | (−1.7) | (−5.1) | (1.0) | (−4.8) |
| Small-minus-big | [−2.1] | [−2.4] | [−0.5] | [−1.0] | [−1.7] | [−0.4] | [−2.8] | [−1.9] | [−0.7] | [0.3] | [−1.9] | [−2.3] |
| Low payout ratio | −0.73 | −0.69 | −0.09 | −1.68 | −0.05 | −0.44 | −0.73 | −0.60 | −0.07 | −1.09 | −0.06 | −0.55 |
| | (−4.5) | (−6.6) | (−4.4) | (−5.4) | (−1.4) | (−3.9) | (−5.2) | (−7.0) | (−4.3) | (−3.8) | (−1.9) | (−5.5) |
| High payout ratio | −0.37 | −0.44 | −0.06 | −1.76 | −0.02 | −0.39 | −0.25 | −0.36 | −0.05 | −1.33 | −0.01 | −0.49 |
| | (−2.0) | (−3.8) | (−2.8) | (−5.3) | (−0.5) | (−3.9) | (−1.5) | (−3.3) | (−2.5) | (−4.6) | (−0.3) | (−5.9) |
| Low-minus-high | [−1.6] | [−2.0] | [−0.8] | [0.2] | [−0.8] | [−0.5] | [−2.5] | [−1.9] | [−0.8] | [0.7] | [−1.2] | [−0.5] |
| With bond rating | −0.28 | −0.40 | −0.06 | −1.95 | −0.04 | −0.32 | −0.31 | −0.37 | −0.05 | −1.31 | −0.05 | −0.42 |
| | (−1.5) | (−3.5) | (−3.1) | (−6.2) | (−1.2) | (−2.6) | (−2.0) | (−3.6) | (−2.7) | (−5.1) | (−1.8) | (−4.8) |
| Without bond rating | −0.76 | −0.77 | −0.10 | −2.26 | 0.01 | −0.45 | −0.71 | −0.69 | −0.08 | −1.46 | −0.01 | −0.63 |
| | (−5.4) | (−8.0) | (−6.6) | (−7.3) | (0.3) | (−4.4) | (−5.6) | (−8.3) | (−5.9) | (−5.7) | (−0.4) | (−7.0) |
| Without-minus-with | [−3.1] | [−3.4] | [−1.9] | [−0.9] | [1.5] | [−1.4] | [−2.7] | [−3.1] | [−1.4] | [−0.6] | [1.3] | [−2.4] |

## Table 4 : Slopes from Fama-MacBeth (1973) Cross-Sectional Regressions of Monthly Percent Excess Returns on Anomaly Variables in the Subsamples Split by Limits to Arbitrage Measures and in the Subsamples Split Jointly by Limits to Arbitrage Measures and Financing Constraints Measures (July 1963–December 2008, 558 Months)

We run univariate cross-sectional regressions of monthly percent excess returns from July of year $t$ to June of year $t+1$ on a given anomaly variable for the fiscal year ending in calendar year $t-1$ in two subsamples split around the medium of a given measure of limits to arbitrage (in the first two rows) as well as in subsamples split jointly by an independent two by two sort on a given limits to arbitrage measure and a given financing constraints measure (in the remaining rows). We report the slope differences and their Fama-MacBeth $t$-statistics (in brackets) across the subsamples. "H−L idio. volatility" is the difference between idiosyncratic volatility subsamples from a one-way sort. "Small asset, H−L volatility" is the difference between the two idiosyncratic volatility subsamples within the half of the sample consisting of firms with smaller-than-medium asset size. "Low volatility, W/O−W rating" is the difference between subsamples without and with bond ratings within the half of the sample consisting of firms with lower-than-medium idiosyncratic volatility. Other various cuts of the sample are defined similarly. Excess returns are the difference between portfolio returns and one-month Treasury bill rate (from Kenneth French's Web site). For firms with negative earnings but positive payout, we do not calculate their payout ratios but categorize them as least constrained (along with firms with high payout ratios). $I/A$ is investment-to-assets, $\triangle A/A$ is asset growth, $\triangle I/I$ is investment growth, $NSI$ is net stock issues, $ACI$ is abnormal corporate investment, and $NOA$ is net operating assets. See the caption of Table 1 for detailed variable definitions.

| | $I/A$ | $\triangle A/A$ | $\triangle I/I$ | $NSI$ | $ACI$ | $NOA$ |
|---|---|---|---|---|---|---|
| H−L idio. | −0.74 | −0.57 | −0.07 | 0.14 | −0.02 | −0.27 |
| volatility | [−3.9] | [−4.7] | [−2.5] | [0.4] | [−0.4] | [−2.7] |
| Small asset, | −0.58 | −0.49 | −0.02 | 1.06 | 0.03 | −0.17 |
| H−L volatility | [−2.4] | [−2.9] | [−0.5] | [2.1] | [0.6] | [−1.3] |
| Big asset, | −0.48 | −0.36 | −0.09 | 0.38 | 0.00 | −0.24 |
| H−L volatility | [−2.0] | [−2.4] | [−2.2] | [0.9] | [0.0] | [−2.0] |
| Low payout, | −0.40 | −0.42 | −0.04 | 0.57 | 0.07 | −0.17 |
| H−L volatility | [−2.0] | [−3.0] | [−1.2] | [1.3] | [1.5] | [−1.5] |
| High payout, | −0.68 | −0.41 | −0.06 | −0.12 | −0.02 | −0.24 |
| H−L volatility | [−2.7] | [−2.4] | [−1.6] | [−0.2] | [−0.3] | [−1.8] |
| With rating, | −0.70 | −0.48 | −0.07 | 0.00 | −0.08 | −0.12 |
| H−L volatility | [−2.9] | [−3.0] | [−1.7] | [0.0] | [−1.3] | [−0.9] |
| Without rating, | −0.65 | −0.60 | −0.05 | 0.27 | 0.02 | −0.35 |
| H−L volatility | [−2.9] | [−3.9] | [−1.8] | [0.6] | [0.4] | [−3.0] |
| Low volatility, | −0.16 | −0.10 | −0.07 | −0.98 | −0.05 | −0.04 |
| S−B asset | [−0.7] | [−0.6] | [−2.2] | [−2.0] | [−1.1] | [−0.3] |
| High volatility, | −0.26 | −0.23 | 0.00 | −0.30 | −0.02 | 0.03 |
| S−B asset | [−1.1] | [−1.6] | [−0.0] | [−0.7] | [−0.5] | [0.2] |
| Low volatility, | −0.46 | −0.19 | −0.04 | −0.48 | −0.11 | −0.10 |
| L−H payout | [−2.3] | [−1.4] | [−1.3] | [−1.1] | [−2.4] | [−0.9] |
| High volatility, | −0.18 | −0.20 | −0.02 | 0.21 | −0.02 | −0.03 |
| L−H payout | [−0.8] | [−1.3] | [−0.6] | [0.4] | [−0.4] | [−0.2] |
| Low volatility, | −0.24 | −0.17 | −0.05 | −0.30 | −0.02 | 0.15 |
| W/O−W rating | [−1.5] | [−1.3] | [−1.6] | [−0.8] | [−0.4] | [1.5] |
| High volatility, | −0.19 | −0.29 | −0.03 | −0.03 | 0.08 | −0.08 |
| W/O−W rating | [−1.0] | [−2.1] | [−1.2] | [−0.1] | [1.6] | [−0.7] |

| | $I/A$ | $\triangle A/A$ | $\triangle I/I$ | $NSI$ | $ACI$ | $NOA$ |
|---|---|---|---|---|---|---|
| L−H dollar | −0.58 | −0.34 | −0.01 | −0.23 | −0.08 | −0.24 |
| trading volume | [−2.9] | [−2.2] | [−0.5] | [−0.6] | [−1.9] | [−2.0] |
| Small asset, | −0.47 | −0.10 | −0.01 | −0.16 | −0.02 | −0.08 |
| L−H volume | [−1.3] | [−0.4] | [−0.2] | [−0.2] | [−0.3] | [−0.4] |
| Big asset, | 0.12 | −0.13 | −0.01 | −0.16 | −0.03 | 0.06 |
| L−H volume | [0.5] | [−0.6] | [−0.3] | [−0.3] | [−0.6] | [0.4] |
| Low payout, | −0.56 | −0.32 | 0.00 | −0.19 | −0.04 | −0.25 |
| L−H volume | [−2.3] | [−2.0] | [−0.1] | [−0.3] | [−0.7] | [−1.6] |
| High payout, | −0.47 | −0.22 | 0.01 | −0.77 | −0.02 | −0.21 |
| L−H volume | [−2.0] | [−1.2] | [0.3] | [−1.6] | [−0.5] | [−1.4] |
| With rating, | −0.29 | 0.07 | −0.03 | 0.06 | −0.06 | −0.06 |
| L−H volume | [−1.1] | [0.3] | [−0.7] | [0.1] | [−1.2] | [−0.4] |
| Without rating, | −0.52 | −0.39 | 0.00 | −0.33 | −0.11 | −0.23 |
| L−H volume | [−2.1] | [−2.2] | [−0.1] | [−0.7] | [−2.1] | [−1.6] |
| Low volume, | −0.92 | −0.37 | −0.05 | −0.21 | −0.07 | −0.21 |
| S−B asset | [−3.0] | [−1.9] | [−1.2] | [−0.4] | [−1.1] | [−1.1] |
| High volume, | −0.33 | −0.40 | −0.05 | −0.21 | −0.08 | −0.08 |
| S−B asset | [−0.9] | [−1.8] | [−0.9] | [−0.3] | [−1.0] | [−0.4] |
| Low volume, | −0.54 | −0.35 | −0.05 | 0.46 | −0.06 | 0.00 |
| L−H payout | [−1.9] | [−1.9] | [−1.6] | [0.8] | [−1.2] | [0.0] |
| High volume, | −0.45 | −0.25 | −0.04 | −0.12 | −0.04 | 0.04 |
| L−H payout | [−1.8] | [−1.6] | [−0.9] | [−0.3] | [−0.8] | [0.2] |
| Low volume, | −0.62 | −0.75 | −0.03 | −0.71 | 0.04 | −0.23 |
| W/O−W rating | [−2.2] | [−3.8] | [−0.9] | [−1.3] | [0.8] | [−1.4] |
| High volume, | −0.39 | −0.29 | −0.06 | −0.32 | 0.09 | −0.06 |
| W/O−W rating | [−1.8] | [−2.0] | [−1.5] | [−0.7] | [1.7] | [−0.5] |