Cost Behavior and Stock Returns

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Abstract

This paper shows that investors fail to *fully* incorporate cost behavior information into valuation. Firms with higher growth in operating costs generate substantially lower future stock returns. A spread portfolio of long stocks with low cost growth and short stocks with high cost growth earns an average abnormal return of about 12% per year, which cannot been explained by extant factor models and firm characteristics. Mean-variance spanning tests show that an investor can benefit from investing in this spread portfolio in addition to well-known factors. Firms with high cost growth also suffer from deterioration in operating performance. The negative cost growth-return relation is stronger among firms with lower investor attention, higher valuation uncertainty, and higher arbitrage costs, and therefore, mispricing plays an important role.

JEL Classification: G12, G14

Keywords: Operating costs; cost behavior; mispricing; limited attention.

I. INTRODUCTION

It has been well documented that stock prices fail to *fully* incorporate public information in earnings and earnings components. For examples, Ball and Brown (1968), Foster, Olsen, and Shevlin (1984), Bernard and Thomas (1989, 1990), Piotroski (2000), Kothari (2001), Livnat and Mendenhall (2006), and Balakrishnan, Bartov, and Faurel (2010), among others, find that earnings levels and surprises positively predict future stock returns. Swaminathan and Weintrop (1991), Ertimur, Livnat, and Martikainen (2003), and Jegadeesh and Livnat (2006) show that revenues (sales) surprises lead to positive contemporaneous market reaction and post-announcement drift up to six months. At a longer horizon, Lakonishok, Shleifer, and Vishny (1994) show that firms with higher sales growth generate substantially lower returns in the next five years. Sloan (1996), Collins and Hribar (2000), and DeFond and Park (2001) show that accruals negatively predict future stock returns, and they attribute this relation to earnings fixation. Somewhat surprisingly, little research explores whether costs, components of earnings, contain information about future stock returns.[1]

In this paper, we fill the gap by investigating the relation between operating costs and future stock returns and operating performance. To this end, we propose a simple cost behavior measure, cost growth, defined as the year-to-year percentage change in a firm's total operating costs (the sum of costs of goods sold, COGS, and selling, general, and administrative expenses, XSGA), and explore the predictability of cost growth on future stock returns. Over the sample period 1968–2013, we find that cost growth is a strong and negative predictor of the cross section of future stock returns. Sorting by firm's pervious-year cost growth, the average raw return of the equal-weighted lowest cost growth decile is 19% per year, while the average return of the highest cost growth decile is as low as 5.5% per year, which means that a spread portfolio that goes long the lowest cost growth decile and short the highest cost growth decile generates an average return of about 13.5% per year.

[1]In the cost accounting literature, Anderson, Banker, and Janakiraman (2003) and Chen, Lu, and Sougiannis (2012) show that costs exhibit sticky behavior that increases in costs have long-lasting and negative effects on a firm's future profitability. Weiss (2010) finds that analysts have less accurate earnings forecasts for firms with more sticky cost behavior. Banker and Chen (2006) and Banker, Chen, and Park (2014) show that cost behavior helps forecast future earnings.

The return on the cost growth spread portfolio cannot been explained by extant risk factors and firm characteristics. The average abnormal return is about 12% per year based on Fama and French's (1993) three-factor model, and it remains large and significant after controlling for more factors like the momentum, liquidity, quality, investment, and profitability factors (Carhart 1997; Pástor and Stambaugh 2003; Asness, Frazzini, and Pedersen 2014; Fama and French 2015). Chen, Roll, and Ross's (1986) five macroeconomic factor model cannot explain the cost growth effect either. In the Fama-MacBeth cross-sectional regressions, we control for a number of important firm characteristics such as firm size (Banz 1981), book-to-market ratio (Fama and French 1993), momentum (Jegadeesh and Titman 1993), reversal (Jegadeesh 1991), industry dummies, and industry adjustment (Fama and Frnech 1997). We find that the forecasting power of cost growth remains large and significant, and is economically comparable with firm characteristics like size, value, and momentum. Moreover, while Hou, Xue, and Zhang (2015) show that their four factors explain almost 85 known anomalies, we find that their model is silent for our new cost growth anomaly based on accounting information.

Cost growth contains additional information beyond earnings surprises and profitability. We compare cost growth with five popular earnings-related measures, including earnings surprises based on quarterly earnings ($\mathrm{SUE_Q}$), earnings surprises based on annual earnings ($\mathrm{SUE_A}$), gross profit (GP), return on asset (ROA), and return on equity (ROE), which are extensively explored by Ball and Brown (1968), Foster, Olsen, and Shevlin (1984), Bernard and Thomas (1989, 1990), Livnat and Mendenhall (2006), Novy-Marx (2013), Fama and French (2015), and Hou, Xue, and Zhang (2015). We find that the regression coefficients on cost growth remain statistically and economically significant after including these controls.

Lakonishok, Shleifer, and Vishny (1994) show that firms with high sales growth generate low returns. We find that cost growth dominates sales growth in forecasting stock returns: costs growth remains significant after controlling for sales growth, whereas sales growth turns out to be insignificant. In this sense, once investors consider the cost growth effect, the sales growth effect becomes redundant and does not add any additional economic value in investment, implying that investors are more likely to misvalue relevant information in costs than sales, since the former is less salient and more uncertain.

In further tests, we find that the cost growth effect is robust after controlling for six important asset growth- and investment-related return determinants. Specifically, we compare cost growth with the accruals (Sloan 1996), net operating assets (Hirshleifer, Hou, Teoh, and Zhang 2004), investment-to-asset (Lyandres, Sun, and Zhang 2008), asset growth (Cooper, Gulen, and Schill 2008), investment growth (Xing 2008), and abnormal capital investment (Titman, Wei, and Xie 2004). We find that the negative cost growth effect remains significant in the Fama-MacBeth regressions and therefore, cost growth contains distinct incremental information about future stock returns.

In addition, our findings are robust to alternative definitions of operating costs like including depreciation and amortization expenses, excluding R&D expenses, scaling changes in costs with alternative deflators such as lagged total asset, or calculating the total operating costs indirectly as the difference between sales and earnings.

What is the investment value of the cost growth return? Unlike existing anomaly studies that focus only on alphas, we examine the investment value of the cost growth return to a portfolio manager who manages a well diversified portfolio of the market and some well known factors. We find that the cost growth spread portfolio improves the mean-variance frontier of investment opportunity significantly. In other words, the cost growth spread portfolio can not only stand alone as an abnormal investment asset, but also adds value to a well diversified portfolio so that its economic importance cannot be ignored. The intuitive reason is that it provides an excellent hedge for the market portfolio (their correlation is -0.29). Interestingly, the cost growth spread portfolio generates consistently positive returns in 42 out of 46 years over our sample period, and it even yields a positive return, although small, in 2008 in the midst of the market crash. The outperformance of the spread portfolio persists well beyond the first year and lasts up to about five years after portfolio formation.

Why are there abnormal returns on the cost growth spread portfolio? We argue that investors may be prone to display behavioral biases when processing information related to cost behavior. Indeed, Fiske and Taylor (1991) and Libby, Bloomfield, and Nelson (2002) find that investors tend to value a firm only based on a few salient variables such as earnings rather than performing a complete analysis of all relevant variables in financial statements, even if some less salient components like cost growth may contain additional information beyond earnings. This is consistent with the fact that financial analysts concentrate most of their attention on earnings and financial economists are more concerned with dividends and cash flows. In addition, since sticky costs make firm's future profit forecasts more uncertainty, investors tend to underreact to costs information.

To explore further mispricing explanation, we consider a four-factor model by augmenting the well-known Fama and French's (1993) three factors with Hirshleifer and Jiang's (2010) mispricing factor. Interestingly, the four-factor model can explain about half of the cost growth abnormal return by reducing its alpha to 5% per annum from an earlier value of 12%. Although the 5% alpha is still statistically significant, the finding suggests that market misvaluation and irrational investor perceptions seem to play an important role in explaining the cost growth effect.

We further examine the mispricing-based explanation with various proxies for limited investor attention, valuation uncertainty, and arbitrage costs. Specifically, according to the recent psychology and asset pricing literature, firms with less attention from investors should have more sluggish market reactions to information embedded in cost growth; moreover, the underreaction to cost growth should be more pronounced when the valuation uncertainty is high (which places a greater cognitive burden on investors and leaves more room for mispricing); and lastly, the limits to arbitrage theory suggests that the underreaction to cost growth is more likely to be sustained in firms with high arbitrage costs. Empirically, the Fama-MacBeth regressions show that the cost growth effect is stronger among firms that are with less investor attention (i.e., smaller caps, lower analyst coverage), higher valuation uncertainty (i.e., higher idiosyncratic volatility, younger age), and higher arbitrage costs (i.e., lower price, higher Amihud (2002) illiquidity, and lower dollar volume).

The mispricing-based interpretation is consistent with the recent literature on the post earnings announcement drift (PEAD) effect. Bartov, Radhakrishnan, Krinsky (2000), Hirshleifer and Teoh (2003), Peng and Xiong (2006), and Hirshleifer, Lim, and Teoh (2009), among others, suggest that limited investor attention causes market underreaction to earnings information and induces return predictability. Liang (2003) and Francis, LaFond, Olsson, and Schipper (2007) show that uncertainty contributes to earnings drift, and investor biases are more pronounced in cases of greater information uncertainty (Daniel, Hirshleifer, and Subrahmanyam 1998; Zhang 2006). In short, our interpretation is in line with the literature that mispricing arises from investors' underreaction to earnings information (e.g., Bernard and Thomas 1989, 1990).

This paper contributes to the growing body of literature that operating costs contain incremental valuation-relevant information beyond earnings. Lipe (1986) finds that the contemporaneous stock price reacts strongly to five cost components. Swaminathan and Weintrop (1991) detect negative contemporaneous stock price reactions to costs surprises using two-day cumulative announcement returns. Ertimur, Livnat, and Martikainen (2003) further compare differential contemporaneous market reactions to sales and cost surprises using three-day cumulative returns centered on preliminary earnings announcement date. Anderson, Banker, Huang, and Janakiraman (2007) find that investors seem to misinterpret sticky cost behavior in SG&A as a signal of poor managerial control. However, most existing studies focus on the contemporaneous relationship around the earnings announcement events, and there is little research that explicitly examines the *predictive* relationship between cost behavior and future stock returns. Indeed, in their recent reviews on variables forecasting the cross section of stock returns, Green, Hand, and Zhang (2013, 2014), Chordia, Subrahmanyam, and Tong (2014), McLean and Pontiff (2015), and Harvey, Liu, and Zhu (2015) list hundreds of firm characteristics and risks, but none of them explicitly considers pricing information in operating costs.

The rest of this paper is organized as follows. Section II discusses the data and the summary statistics of key variables used in this paper. Section III shows that cost growth negatively predicts future stock returns using both portfolio sorts and Fama-MacBeth regressions. Section IV explores the potential economic explanations for the cost growth effect. Section V concludes.

II. DATA AND SUMMARY STATISTICS

We obtain annual accounting data from Compustat and monthly stock returns data from the Center for Research in Security Prices (CRSP). We also obtain analyst coverage data from I/B/E/S. We use the one-month Treasury bill rate from Ken French's web site as the risk-free rate. We consider all domestic common stocks trading on the New York Stock Exchange (NYSE), American Stock Exchange (Amex), and Nasdaq stock markets with accounting and returns data available. Following Fama and French (1993), we exclude the closed-end funds, trusts, American Depository Receipts (ADRs), Real Estate Investment Trusts (REITs), units of beneficial interest, and financial firms that have four-digit standard industry classification (SIC) codes between 6000 and 6999. We also exclude firms with negative book value of equity.[2] We require firms to be listed on Compustat for two years before including them in our sample to mitigate backfilling biases. To ensure a reasonable number of firms in our early sample, we restrict the sample period to be 1963–2012 for accounting data and July 1968 to December 2013 (546 months) for stock returns, since some of our tests require five-years of prior accounting data. To reduce the impact of outliers, we winsorize all variables at the 1% and 99% levels, throughout the paper.

Our main explanatory variable, cost growth (CG) in calendar year t, is defined as the year-to-year percentage change in a firm's total annual operating costs (OC) from the fiscal year ending in calendar year $t-1$ to the fiscal year ending in calendar year t,

$$\mathrm{CG}_t = \frac{\mathrm{OC}_t - \mathrm{OC}_{t-1}}{\mathrm{OC}_{t-1}}. \tag{1}$$

The operating costs (OC) is the sum of costs of goods sold (COGS) and selling, general, and

[2] Following Fama and French (1993), we calculate the book value of equity as shareholders' equity (SEQ), plus balance sheet deferred taxes and investment tax credits (TXDITC) if available, and minus the book value of preferred stock. We set missing values of TXDITC equal to zero. To calculate the value of preferred stock, we set it equal to the redemption value (PSTKRV) if available, the liquidating value (PSTKL) if available, or the par value (PSTK), in that order. If SEQ is missing, we set stockholder' equity equal to the value of common equity plus the par value of preferred stock (CEQ+PSTK) if available, or total assets minus total liabilities (AT-LT), in that order.

administrative expenses (XSGA), following the standard textbook like Penman (2012),

$$\text{OC}_t = \text{COGS}_t + \text{XSGA}_t. \tag{2}$$

To include a firm's CG_t in our sample, it must have positive nonmissing operating costs in both years t and $t-1$. According to the U.S. Generally Accepted Accounting Principles (GAAP) and Compustat, COGS represents all costs that are directly related to the cost of merchandise purchased or the cost of goods manufactured and sold to customers, such as raw materials and direct labor. XSGA includes all operation costs incurred in the regular course of business pertaining to the securing of operating income but not directly related to product production, such as corporate expenses, advertisement expenses, and amortization of research and development (R&D) expenses.

In this paper, we focus on total operating costs, OC, since it includes all the major operating costs of running a business beyond specific cost components like COGS or XSGA alone. Moreover, the accounting classification of COGS and XSGA may be subject to managerial judgment, which may introduce bias into the cost growth estimate of specific costs components. Our cost growth measure (OC) then provides broad insights into the relationship between cost behavior and future stock returns. In Section III Table 8, we show that our results are robust to a bunch of alternative definitions of operating costs.

To avoid look-ahead bias and ensure that the accounting information is publicly known before we use it, following Fama and French (1993), we allow for a minimum 6-month lag between stock returns and lagged accounting-based variables. At the end of June of each year $t+1$, we sort firms into ten deciles based on cost growth (CG) for fiscal year ending in calendar year t, as defined in Equations (1) and (2). We then match the accounting data to a firm's stock returns from July of year $t+1$ to June of year $t+2$. Our sample spans the period from 1962 to 2012 for accounting data and the period from July 1968 to December 2013 for stock returns, since some of our tests require five-years of prior accounting data.

Panel A of Table 1 reports the averages of annual firm characteristics at the portfolio level, including cost growth (CG), market equity (ME),[3] book to market ratio (B/M), momentum ($r_{-12,-1}$), sales growth (SG), operating accruals (ACC), investment to asset (INV), and asset growth (AG). ME is the year-end market equity value in year t. B/M is defined as in Fama and French (1993), where book equity is the Compustat book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit, minus book value of preferred stock (in the following order: redemption, liquidation, or par value) in fiscal year ending in calendar year t and market equity is CRSP price per share times the number of shares outstanding at the end of year t. $r_{-12,-1}$ is calculated as the cumulative stock return in year t. SG is defined as the annual percentage change in sales from year $t-1$ to year t. ACC is defined as the change in noncash current assets less the change in current liabilities excluding the change in short-term debt and the change in taxes payable minus depreciation and amortization expense deflated by average total assets. INV is calculated as the change in gross property, plant, and equipment plus the change in inventories scaled by lagged total assets. AG is calculated as the annual percentage change in total assets.

Panel A shows that there are significant variations in cost growth rates across the deciles. The average annual percentage for the highest cost growth decile (decile 10) is 0.96, while the counterpart for the lowest cost growth decile (decile 1) is −0.25. For market equity, the middle cost growth firms (decile 6) have the highest market size ($189 million), while the highest (decile 10) and lowest (decile 1) cost growth firms have lower market size of $133 and $42 million, respectively. In addition, higher cost growth firms tend to have lower book-to-market ratio (growth firms), higher momentum, higher sales growth, higher operating accruals, higher investment, and higher asset growth.

Panel B of Table 1 reports the annual average operating performance, including gross profit (GP), profit margin (PM), return on asset (ROA), cash flow (CF), and changes in PM, ROA, and CF (ΔPM, ΔROA, and ΔCF). GP is calculated as the annual gross profit (revenue minus costs of goods sold) scaled by total assets. PM is defined as income before extraordinary items divided by sales. ROA is defined as income before extraordinary items divided by total assets. CF is defined as net income plus amortization and depreciation minus changes in working capital and capital expenditures divided by

[3] We report the annual median rather than average, since market equity (ME) is highly skewed within each portfolio.

total assets. ΔPM (ΔROA, ΔCF) is defined the annual change in PM (ROA, CF) from year $t-1$ to year t.

Panel B reveals two interesting facts. First, there is an inverted-U shaped pattern between cost growth and the *level* of operating performance. For example, for profit margin (PM), middle cost growth firms tend to have the highest profitability levels (for example, 0.04 for decile 6), whereas highest and lowest cost growth firms have the lowest profitability levels (-0.20 for decile 1 and -0.23 for decile 10). Similar inverted-U shaped patterns apply to gross profit, return on asset, and cash flow levels. Second, the *change* of operating performance is decreasing with respect to cost growth. The operating performance change like ΔPM (ΔROA, ΔCF) monotonically decreases from 0.10 (0.05, 0.05) for decile 1 to -0.29 (-0.05, -0.05) for decile 10 in general. Hence, firms that high operating costs growth are experiencing lower profitability changes. This negative relation suggests a negative relation between cost growth and subsequent operating performance, which we examine further in Section IV.

III. EMPIRICAL RESULTS

We investigate the relation between cost growth and future stock returns by using two approaches commonly used in the literature. First, we sort firms and form portfolios based on cost growth. Second, we perform cross-sectional regressions along the lines of Fama and MacBeth (1973).

Portfolio sorts on cost growth

In this subsection, we form decile portfolios sorted by cost growth and examine whether their performance can be explained by extant factor models. Specifically, at the end of June of each year $t+1$, we form ten decile portfolios based on lagged cost growth rates for the fiscal year ending in calendar year t. We hold these portfolios for one year, from July of year $t+1$ to June of year $t+2$, and compute the equal-weighted monthly returns of these cost growth decile portfolios. Decile 1 refers to firms in the lowest cost growth decile, and decile 10 refers to firms in the highest cost growth decile. "Low-High" refers to the cost growth spread portfolio that goes long the lowest cost growth decile portfolio and short the highest cost growth decile portfolio.

Panel A of Table 2 shows that the monthly average raw returns of the decile portfolios are generally decreasing with respect to cost growth, from 1.57% for the lowest cost growth decile to 0.45% for the highest cost growth decile. The average return of the spread portfolio is 1.12% per month, with a t-statistic of 8.14, suggesting that a trading strategy that buys the lowest cost growth decile and sells the highest cost growth decile will earn an average return of roughly 13% per year.

We then examine whether the negative cost growth-return relation can be explained by the well-known Fama and French (1993) three-factor model. We compute the alphas (abnormal returns) and factor loadings by regressing the time series of monthly excess portfolio returns of cost growth deciles on the three factors, including market (MKT), size (SMB), and value (HML).[4] We find that firms with low cost growth are underpriced with positive alphas, whereas firms with high cost growth are overpriced with negative alphas. For example, the lowest cost growth decile has a monthly alpha of 0.30% ($t = 2.02$), whereas the highest cost growth decile has a monthly alpha of -0.68% ($t = -4.42$). The alpha of the cost growth spread portfolio is 0.98% with a t-statistic of 8.08. This indicates that the long-short strategy earns an abnormal return of roughly 12% per year. Harvey, Liu, and Zhu (2015) recently raise the data mining concern on anomaly discovery and suggest a higher hurdle with a t-statistic greater than 3 in testing that the average return of a spread portfolio of the newly discovered anomaly is zero. They also argue that anomalies based on economic theories are more meaningful. Regarding this paper, operating costs are linked to the standard earnings identity and accounting valuation theory, and the abnormal return of the cost growth spread portfolio passes the high t-statistic hurdle.

The loadings on the Fama-French market and size factors are significant but generally flat across the deciles. The loadings on the value factor generally decrease from 0.37 for the lowest cost growth

[4] We thank Ken French for making the data public.

decile to −0.11 for the highest cost growth decile portfolio, indicating that low cost growth firms tend to be value firms. The cost growth spread portfolio loads negatively on the market factor (−0.14) and positively on the size and value factors (0.16 and 0.48, respectively). These far less than one loadings suggest that the spread portfolio is not heavily exposed to the risks of the three factors.

Panel B of Table 2 reports high abnormal returns ranging from 0.70% to 1.07% per month for the cost growth spread portfolio, when we augment the Fama-French three factors with momentum (Carhart 1997), liquidity (Pastor and Stambaugh 2003), quality (Asness, Frazzini and Pedersen 2014), or investment and profitability (Fama and French 2015). We also explore Hou, Xue, and Zhang's (2015) market, size, investment, and profitability four-factor model. In one word, these models do not exhibit any potential to explain the average returns of cost growth portfolios.

Finally, we explore whether macroeconomic risks can explain the cost growth portfolios. In so doing, we employ Chen, Roll, and Ross (1986) (CRR hereafter) model, which includes five factors such as the growth rate of industrial produciton (MP), unexpected inflation (UI), change in expected inflation (DEI), term structure of interest rate (UTS), and default risk (UPR) factors. Since the first three macroeconomic risk factors (MP, UI, and DEI) are not tradable, we employ the mimicking factor method to track these factors, following Liu and Zhang (2008) and Cooper and Priestley (2011).[5] Panel B of Table 2 shows that the CRR model generates a large average monthly abnormal return of 1.07% for the cost growth spread portfolio with a t-statistic of 7.63. The scale of this mispricing error is similar to that of the Fama-French three-factor model, suggesting that the spread portfolio is not captured by macroeconomic risks.

Figure 1 plots the average annual raw and abnormal returns of the cost growth spread portfolio in the subsequent five years following portfolio formation. The abnormal returns are computed as the intercepts from the time series regressions of the spread portfolio returns on the Fama-French three

[5] For consistency, we construct mimicking factors for all the five CRR macroeconomic risk factors, although the UTS and UPR factors are traded assets. The basis of the mimicking portfolios consist of 40 test portfolios: 10 size deciels, 10 book-to-market deciles, 10 momentum deciles, and 10 cost growth portfolios, all of which are based on one-way sorts. The size, book-to-market, and momentum test portfolios have been widely used in the asset pricing literature. We include cost growth portfolios because we want to understand the driving forces for the negative cost growth premium.

factors. At the end of June of each year $t+1$ (event-year 0), we sort firms into cost growth deciles based on cost growth rates in fiscal year ending in calendar year t. We hold these decile portfolios for five years, from July of year $t+1$ to June of year $t+6$, and compute the equal-weighted monthly returns for these portfolios. The average annual returns of the portfolios formed in June of year $t+1$ and held from the July of year $t+1$ to June of year $t+2$ are labeled as event-year 1, and from the July of year $t+2$ to June of year $t+3$ are labeled as event-year 2, etc.

Figure 1 shows that firms in the lowest cost growth decile consistently generate higher returns than firms in the highest cost growth decile for five years in term of both raw and abnormal returns. The average raw and abnormal returns of the cost growth spread portfolio are positive and large, with virtually no reversal. This finding suggests that the market underreacts to negative valuation information in cost growth, consistent with the PEAD effect where mispricing arises from investors' underreaction to earnings information (e.g., Bernard and Thomas 1989, 1990). It also suggests that the market takes several years to fully incorporate the valuation information about a firm's fundamentals embedded in cost growth.

Overall, our cost behavior measure, cost growth, appears to be a negative predictor for future stock returns in the cross section. A simple cost growth strategy of going long low cost growth stocks and short high cost growth stocks can generate sizeable abnormal returns that cannot be explained by extant risk factors.

Double sorts on size and cost growth

In this subsection, we analyze the performance of portfolios double sorted on market capitalization and cost growth, and show that the forecasting power of cost growth is robust across firm size and is not driven by microcap stocks.

Following Fama and French (2006), portfolios are formed by performing independent double sorts by market capitalization and cost growth. Specifically, at the end of June of each year $t+1$, we independently sort firms into three size groups (small, middle, and large) using the 20^{th} and 50^{th}

NYSE market equity percentiles in June of year $t+1$ and five cost growth quintiles based on cost growth in fiscal year ending in calendar year t. We hold these portfolios for one year, from July of year $t+1$ to June of year $t+2$, and compute the equal-weighted monthly returns of these 15 (3×5) size-cost growth portfolios. We focus on five cost growth quintile portfolios due to limited space constraint; however, in unreported tables, we obtain even stronger results when we double sorts firms into ten cost growth deciles.

Table 3 reports the average raw returns of the double sorts on size and cost growth, the average abnormal returns, the factor loadings, and their corresponding t-statistics from regressing the excess returns on the Fama-French three factors over the 1968:07–2013:12 period. Firms below the 20% break point are denoted as "Small"; firms between the 20% and 50% break points are denoted as "Middle"; and firms above the 50% break point are denoted as "Large".

Table 3 reveals that the cost growth effect exists across all three size groups. While the negative cost growth-return relationship is much stronger for firms with small capitalizations, it remains significant among the middle and large size firms. For example, for the small size firms, the cost growth spread portfolio has a monthly average raw return of 0.84% ($t = 7.98$) and a monthly average Fama-French three-factor alpha of 0.79% ($t = 8.01$). For the middle size firms, the spread portfolio has a monthly average raw return of 0.49% ($t = 3.63$) and a monthly alpha of 0.32% ($t = 2.81$). For the large size firms, the spread portfolio has a monthly average raw return of 0.44% ($t = 2.94$) and a monthly alpha of 0.27% ($t = 2.24$). In sum, the cost growth effect is present among all size groups and is not an exclusive characteristic of the small size firms.

Controlling for firm characteristics

In this subsection, we employ the Fama-MacBeth approach (Fama and MacBeth, 1973) to investigate that wether the cost growth effect is driven by firm characteristics. Particularly, we compare cost growth with firm size (Banz 1981), book-to-market ratio (Fama and French 1993), momentum (Jegadeesh and Titman 1993), monthly reversal (Jegadeesh 1990), and industry fixed effects based on the 48 industry classifications defined in Fama and French (1997) (to control for any industry-specific characteristics).

Table 4 reports the regression coefficients and their t-statistics with the Fama-MacBeth regression. Column 1 shows the predictive power of cost growth without any control. The coefficient on cost growth is -0.897 with a t-statistic of -8.24. After controlling for size and book-to-market ratio (Column 2), the regression coefficient is -0.642 with a t-statistic of -6.94. When we further control for the momentum and reversal effects (Column 3), the regression coefficient remains -0.665 ($t = -8.24$). The regression coefficients on firm characteristics are generally consistent with previous literature. Size and reversal are negative predictors of future stock returns, whereas book-to-market ratio and momentum are positive predictors.

Columns 4 to 6 of Table 4 show that the industry fixed effect does not subsume the predictive power of cost growth. While the t-statistics of cost growth become larger in absolute value than the corresponding ones without controlling for industry dummies, the regression coefficients are generally unchanged. Column 7 considers the case when cost growth is demeaned by industry. Interestingly, since industry adjustment may remove industry-level shocks, cost growth displays stronger power in forecasting stock returns, with a t-statistic of -9.62. Summarizing Table 4, we conclude that the negative cost growth effect is robust after controlling for size, book-to-market, momentum, reversal, and industry fixed effects.

Comparing with profitability-related characteristics

Since earnings are equal to sales minus costs, the cost growth effect may be driven by earnings-related characteristics. To alleviate this concern, we control for five firms earnings-related characteristics in the Fama-MacBeth regression. The first is the quarterly standardized unexpected earnings ($\mathrm{SUE_Q}$), calculated as the most recently announced quarterly earnings minus the quarterly earnings four quarters ago, standardized by its standard deviation estimated over the prior eight quarters, which is used to proxy for earnings surprises in Ball and Brown (1968), Foster, Olsen, and Shevlin (1984), and Bernard and Thomas (1989, 1990). The second is the annual standardized unexpected earnings (SUE_A) and is calculated as the annual earnings per share before extraordinary items (EPS) in the fiscal year ending in calendar year t minus the annual EPS one year ago in year $t-1$, standardized by the stock price per share at the end of year t (Livnat and Mendenhall 2006). The third and forth are the gross profitability (GP) and the return on asset (ROA), defined in the previous section. The fifth and last is the return on equity (ROE), calculated as the annual income before extraordinary items (IB) in fiscal year ending in calendar year t scaled by book value of equity (Novy-Marx 2013). All of them are positively associated with subsequent stock returns.

In Table 5, we run the Fama-MacBeth regression of monthly stock returns on lagged cost growth and each of the five earnings-characteristics. Similar to Table 4, we also control for size, book-to-market ratio, momentum, and reversal. The regression coefficient on cost growth is -0.604 ($t = -3.82$) after controlling for quarterly earnings surprises SUE_Q, -0.666 ($t = -8.40$) after controlling for annual earnings surprises SUE_A, -0.606 ($t = -7.52$) after controlling for gross profit GP, -0.675 ($t = -8.65$) after controlling for return of asset ROA, and -0.678 ($t = -8.58$) after controlling for return on equity ROE, respectively. We do not report results by including all the controls in a single kitchen-sink regression model due to the serious multicollinearity problem. Therefore, cost growth contains unique and incremental forecasting information beyond that contained in other commonly known variables related to earnings and profitability.

Comparing with sales growth

Lakonishok, Shleifer, and Vishny (1994) show that firms with high sales growth generate substantially lower returns due to investors over-extrapolation of past gains. In this subsection, we compare the negative cost growth effect with the sales growth effect by employing a “sales growth” versus “production efficiency” decomposition.

In the spirit of Richardson, Sloan, Soliman, and Tuna (2006), we decompose cost growth (CG) into sales growth (SG) minus the change in markup (ΔMU) minus the interaction between sales growth and change in markup ($SG * \Delta MU$),

$$\mathrm{CG}_t \equiv \mathrm{SG}_t - \Delta\mathrm{MU}_t - \mathrm{SG}_t * \Delta\mathrm{MU}_t. \tag{3}$$

The sales growth rate, SG_t, is defined as the percentage change in sales (REVT) from fiscal year ending in calendar year $t-1$ to fiscal year ending in calendar year t,

$$\mathrm{SG}_{t-1} = \frac{\mathrm{REVT}_{t-1} - \mathrm{REVT}_{t-2}}{\mathrm{REVT}_{t-2}}. \tag{4}$$

$\Delta\mathrm{MU}_t$ denotes the change in percentage markup (MU) from fiscal year ending in calendar year $t-1$ to fiscal year ending in calendar year t scaled by markup in year t,

$$\Delta\mathrm{MU}_t = \frac{\mathrm{MU}_t - \mathrm{MU}_{t-1}}{\mathrm{MU}_t} = \frac{(\mathrm{REVT}_t/\mathrm{OC}_t) - (\mathrm{REVT}_{t-1}/\mathrm{OC}_{t-1})}{\mathrm{REVT}_t/\mathrm{OC}_t}, \tag{5}$$

where markup (MU) is the ratio of sales (REVT) to operating costs (OC).

Intuitively, based on the cost behavior model in management accounting (Garrison and Noreen 2002), firms with high cost growth may experience high growth in sales (outputs) or reduction in production efficiency (profitability). For example, if efficiency remains unchanged, sales growth will lead to growth in operating costs. On the other hand, in the absence of sales growth, reductions in efficiency will lead to growth in operating costs to generate the same level of outputs. In the decomposition (3), SG_t reflects the component of cost growth that is attributable to sales growth, and $\Delta\mathrm{MU}_t$ then reflects the component of cost growth that is attributable to less efficient use of inputs. The decomposition also contains an interaction term, indicating that a simple linear decomposition is not appropriate when sales growth and efficiency changes are correlated. Empirically, we show that sales growth (SG_t) and change in markup ($\Delta\mathrm{MU}_t$) are positively correlated, indicating that firms with increases in sales growth tend to experience increases in production efficiency.[6] Therefore,

[6]Economies of scale imply a positive correlation between sales growth and change in efficiency, because increases in sales lead to lower marginal operating costs, thus higher efficiency. Sticky costs imply a positive correlation too, because costs saving will be limited, when sales decrease, leading to lower efficiency and earnings.

our decomposition is an algebraic identity and helps mitigate the estimation error concern (e.g., the sensitivity of cost growth to sales growth) and the misspecificatin concern (e.g., the nonlinear interaction between sales growth and change in efficiency) for statistically oriented regression specifications.

Table 6 reports the results for the Fama-MacBeth regressions of monthly stock returns on sales growth versus production efficiency decomposition of lagged cost growth, and compares the forecasting power of cost growth with sales growth. Column 1 of Table 6 reports the forecasting performance of cost growth as a benchmark. Columns 2 to 4 conduct the pairwise Fama-MacBeth regressions, where each of the sales growth, change in markup, and the interaction components is added into the regression one-by-one together with cost growth. We find that the predictive power of cost growth remains strong and significant after controlling for all these three components. In contrast, sales growth, change in markup, and the interaction term are not significant then. Thus, the forecasting power in sales growth is subsumed by cost growth, which contains not only the information in sales growth but also the information contained in production efficiency.

Comparing with investment and growth-related determinants

In this subsection, we compare cost growth with accruals (Sloan 1996), net operating assets (Hirshleifer, Hou, Teoh, and Zhang 2004), investment to assets (Lyandres, Sun, and Zhang 2008), asset growth (Cooper, Gulen, and Schill 2008), investment growth (Xing 2008), and capital investment (Titman, Wei, and Xie 2004), all of which are related to investment and asset growth, and are negative predictors of the cross section of stock returns. Accruals (ACC) is calculated as operating accruals deflated by average total assets. Net operating assets (NOA) is calculated as net operating assets (operating assets minus operating liabilities) scaled by lagged total assets, where operating assets are calculated as total assets minus cash and short-term investment, and operating liabilities are calculated as total assets minus debt included in current liabilities minus long-term debt minus minority interests minus preferred stocks minus common equity. Investment to assets (INV) is calculated as the annual change in gross property, plant, and equipment plus the change in inventories scaled by lagged total assets. Asset growth (AG) is the annual percentage change in total assets. Investment growth (IG) is calculated as the growth rate of capital expenditure. Capital investment (CI) is calculated as the current year's capital expenditure divided by the past 3-year moving average of capital expenditure, where capital expenditure is scaled by its sales.

In Table 7, we run the Fama-MacBeth regressions of monthly stock returns on lagged cost growth and each of the six controls of investment and growth variables. Again, we do not report results for the kitchen-sink model of including all the controls in a single regression, due to the serious multicollinearity problem. The regression coefficient on cost growth is -0.534 ($t = -6.33$) after controlling for accruals, -0.421 ($t = -5.24$) after controlling for net operating assets, -0.427 ($t = -5.00$) after controlling for investment to assets, -0.386 ($t = -3.39$) after controlling for asset growth, -0.502 ($t = -5.82$) after controlling for investment growth, and -0.571 ($t = -6.48$) after controlling for abnormal capital investment, respectively. In sum, Table 7 suggests that cost growth contains unique and incremental forecasting information for future stock returns, beyond that contained in other variables related to investment and asset growth.

Alternative measures of cost growth

In this subsection, we show that our finding is robust to alternative definitions of cost growth. First, our operating costs measure, OC in Equation (2), includes all the major operating costs of running a business beyond specific individual cost components such as the costs of goods sold (COGS) and selling, general, and administration expenses (XSGA). Hence, the OC measure provides broad insights into the relationship between cost behavior and stock returns (e.g., Weiss 2010). However, the accounting classification may be subject to managerial judgment that can introduce bias into the estimate of specific cost components like COGS and XSGA. For example, Anderson, Banker, and Janakiraman (2003), among others, show that COGS is less sticky than XSGA and is more likely to be cut as sales decrease, when the firm is in distress or in economic downturns. XSGA is arguably related to fixed costs and is for maintaining business, whereas COGS is arguably related to variable costs and product production. For this reason, we compute the growth rates of the two cost subcategories, the COGS growth (CG_{COGS}) and XSGA growth (CG_{XSGA}). Specifically, we define COGS growth (CG_{COGS}) in year t as the year-to-year percentage change in annual COGS from the fiscal year ending in calendar year $t-1$ to the fiscal year ending in calendar year t, $\text{CG}_{\text{COGS},t} = \frac{\text{COGS}_t - \text{COGS}_{t-1}}{\text{COGS}_{t-1}}$, and XSGA growth ($\text{CG}_{\text{XSGA}}$) as the year-to-year percentage change in annual XSGA from the fiscal year ending in calendar year $t-1$ to the fiscal year ending in calendar year t, $\text{CG}_{\text{XSGA},t} = \frac{\text{XSGA}_t - \text{XSGA}_{t-1}}{\text{XSGA}_{t-1}}$. COGS growth and XSGA growth have a correlation of 0.55 with each other, and they have high correlations of 0.81 and 0.79 with our main cost growth measure CG, respectively.

Columns 2 and 3 of Table 8 show that both COGS growth (CG_{COGS}) and XSGA growth (CG_{XSGA}) are significant predictors of future stock returns, with regression coefficients of -0.446 ($t = -7.83$) and -0.574 ($t = -7.38$), respectively. Column 4 further shows that, when including CG_{COGS} and CG_{XSGA} together in a single regression, both CG_{COGS} and CG_{XSGA} remain significant, with coefficients of -0.307 ($t = -5.37$) and -0.377 ($t = -4.65$), respectively. This finding suggests that firms with high CG_{COGS} and high CG_{XSGA} will underperform in the future, and both variables contain significant incremental information on future stock returns. Moreover, the regression coefficients on CG_{XSGA} are slightly larger in absolute value than those on CG_{COGS} (-0.574 vs. -0.446 and -0.377 vs. -0.307), consistent with Anderson, Banker, and Janakiraman (2003) that XSGA expenses are more sticky than COGS expenses. Taken as a whole, our measure of operating costs is better than the two subcategory measures, because both COGS and XSGA are complementary and jointly predict stock returns.

Second, our operating costs measure in Equation (2) does not include depreciation and amortization expenses, since the depreciation may depend on the accounting rules a firm chooses, which may not be related to the firm's business fundamentals. Capital intensive firms may employ more fixed assets for business operations, leading to higher depreciation and amortization expenses. In this sense, depreciation and amortization expenses can be viewed as parts of a firm's operating costs. As a robustness check, we construct an alternative measure of operating costs, OC_{DP}, which incorporates depreciation and amortization expenses and is defined as the sum of costs of goods sold (COGS), selling, general, and administration expenses (XSGA), and depreciation and amortization expenses (DP), $\mathrm{OC}_{\mathrm{DP},t} = \mathrm{COGS}_t + \mathrm{XSGA}_t + \mathrm{DP}_t$. We then calculate cost growth as $\mathrm{CG}_{\mathrm{DP},t} = \frac{\mathrm{OC}_{\mathrm{DP},t} - \mathrm{OC}_{\mathrm{DP},t-1}}{\mathrm{OC}_{\mathrm{DP},t-1}}$. Column 5 of Table 8 shows that $\mathrm{CG}_{\mathrm{DP}}$ negatively predicts future stock returns with a regression coefficient of -0.597 ($t = -7.67$), which is slightly smaller in absolute value than that in Column 1 where depreciation and amortization expenses (DP) is not included in the calculation of operating costs. In this sense, our operating costs measure is clean and captures the main information in predicting stock returns.

Third, our operating costs measure in Equation (2) includes a firm's R&D expenses (a component of XSGA). According to the reliability criterion, assets can be recognized only if they can be measured with reasonable precision and supported by objective evidence, free of opinion and bias. So the GAAP requires that investments in R&D are expensed immediately in the income statement rather than booked to the balance sheet as intangible assets, since estimates of these assets are uncertain, subjective, and open to managerial manipulation and bias. On the other hand, the result can be a mismatch, since R&D expenses can be regarded as investments in intangible assets to generate future sales. As a robustness check, we construct an alternative measure of operating costs, $\mathrm{OC}_{\mathrm{RD}}$, which excludes R&D expenses and is defined as costs of goods sold (COGS) plus selling, general, and administration expenses (XSGA) minus R&D expenses (XRD), $\mathrm{OC}_{\mathrm{RD},t} = \mathrm{COGS}_t + \mathrm{XSGA}_t - \mathrm{XRD}_t$.[7] Accordingly, we obtain a new cost growth measure, $\mathrm{CG}_{\mathrm{RD},t} = \frac{\mathrm{OC}_{\mathrm{RD},t} - \mathrm{OC}_{\mathrm{RD},t-1}}{\mathrm{OC}_{\mathrm{RD},t-1}}$. Column 6 of Table 8 shows that this new alternative measure $\mathrm{CG}_{\mathrm{RD}}$ is also a strong negative predictor of stock returns, with a regression coefficient of -0.610 ($t = -7.88$). This implies that our operating cost measure is not driven by investments like R&D expenses.

Fourth, we examine the robustness of our finding by scaling the changes in operating costs by alternative deflators. Specifically, we consider an alternative cost growth measure $\mathrm{CG}_{\mathrm{AT}}$, in which we deflate the year-to-year changes in operating costs by lagged total assets (AT) rather than lagged

[7] In unreported results, we obtain similar findings after removing advertising expenses from our operating costs measure.

operating costs (OC), $\mathrm{CG}_{\mathrm{AT},t} = \frac{\mathrm{OC}_t - \mathrm{OC}_{t-1}}{\mathrm{AT}_{t-1}}$. This exercise is to demonstrate that our finding of the negative cost growth effect is robust to different deflators, and is mainly driven by the change in operating costs component ($\mathrm{OC}_t - \mathrm{OC}_{t-1}$) rather than the lagged operating costs component (the deflator, OC_{t-1}). Column 7 of Table 8 shows that the regression coefficient on $\mathrm{CG}_{\mathrm{AT}}$ is -0.457 ($t = -6.49$), which is again comparable to the result in Column 1. In unreported tables, we obtain similar results employing alternative specifications like deflating the changes in operating costs by lagged book values of equity, market values of equity, and sales. All the results indicate that our documented cost growth effect is generally driven by the changes in the operating cost component, and is robust to the choice of denominator.

Lastly, in unreported tables, we obtain similar results when the total operating costs are indirectly defined as the difference between the sales and income before extraordinary items, which may include interest expenses and taxes.

Mean-variance spanning tests

The abnormal return on the cost growth spread portfolio is highly significant both statistically and economically. The question is whether it can add any investment value to an investor who holds a well diversified portfolio, such as the market portfolio or a portfolio of Fama and French (1993) three factors. The spanning test proposed originally by Huberman and Kandel (1987) provides exact the answer we need.

Following Huberman and Kandel (1987), we run time-series regressions of the spread portfolio on various factors,

$$R_{1,t} - R_{10,t} = \alpha + \sum_{i=1}^{n} \beta_i \cdot F_{i,t} + \varepsilon_t, \tag{6}$$

where $R_{1,t}$ and $R_{10,t}$ are the portfolio returns of the lowest and highest cost growth deciles, $F_{i,t}$ (for $i = 1, \ldots, n$) are the returns on various factors such as the Fama-French three factors. The spanning hypothesis is that the spread portfolio can be spanned or replicated in the mean-variance space by the factors.[8] Statistically, the hypothesis amounts to the test of the following restrictions:

$$H_0: \ \alpha = 0 \ \text{ and } \ \sum_{i=1}^{n} \beta_i = 1. \tag{7}$$

Following Kan and Zhou (2012), we carry out six spanning tests: Wald test under conditional homoscedasticity, Wald test under independent and identically distributed (i.i.d.) elliptical distribution, Wald test under conditional heteroscedasticity, Bekerart-Urias spanning test with errors-in-variables (EIV) adjustment, Bekerart-Urias spanning test without the EIV adjustment, and DeSantis spanning test. All six tests have asymptotic Chi-Squared distribution with 2 degrees of freedom.

The results in Table 9 suggest a strong rejection of the hypothesis that the cost growth spread portfolio is inside the mean-variance frontier of existing factor models. This rejection implies that the cost growth spread portfolio can improve the mean-variance frontier of investment opportunity significantly. In other words, the cost growth spread portfolio can not only stand alone as an abnormal investment asset, but also adds value to a well diversified portfolio so that its economic importance cannot be ignored.

The intuitive explanation for the cost growth spread portfolio's high value for investing is that it provides an excellent hedge for the market portfolio. Figure 2 plots the time-series of annual returns of the costs grow spread portfolio and the market portfolio from 1968 to 2013. The cost growth spread portfolio appears to be a good hedge against the market portfolio, because it has a negative correlation of -0.29 with the market and even generates a small positive return in 2008, in stark contrast to the sharp crash of the aggregate market portfolio. In addition, the spread portfolio return is positive in 42 years out of 46, and it does not display a decreasing trend over our sample period, in contrast to Chordia, Subrahmanyam, and Tong (2014) and McLean and Pontiff (2015) who find most anomalies

[8]The mean-variance framework is still the major model used in practice today in asset allocation and active portfolio management despite many other complex models developed by academics, due to its capability of handling real-world issues, such as position limits, characteristic exposures and short-sell constraints (see, e.g., Grinold and Kahn 1999, and Qian, Hua, and Sorensen 2007).

decay or disappear over time. In sum, Table 9 and Figure 2 suggest that investing in the cost growth spread portfolio provides additional benefits to investors to diversify against the market factors risks.

IV. ECONOMIC EXPLANATIONS

We seek to understand the economic forces driving the negative cost growth-return relationship in Section III. We examine the association between cost growth and subsequent operating performance, and evaluate why the market fails to fully recognize the information contained in cost growth.

Cost growth and subsequent operating performance

In this subsection, we explore the relationship between cost growth and subsequent operating performance. The goal here is to assess if high cost growth firms that generate low future returns also experience deterioration in future operating performance.

The basic accounting identity shows that earnings are equal to sales minus costs, suggesting a negative association between cost growth and operating performance. In Table 1, we do find that cost growth is negatively associated with changes in contemporaneous operating performance measures, which is not surprising and consistent with the simple accounting identity of earnings. Moreover, costs are more sticky than sales in that costs decrease less with a sales activity decrease than they increase with an equivalent sales activity increase, since managers may retain idle capacity as product demand falls but add capacity as demand grows (e.g., Anderson, Banker, and Janakiraman, 2003). The cost stickiness also implies that increases in costs forecast reductions in a firm's future operating performance, since future cost saving will be limited even if future sales activity declines, resulting in decreases in earnings (Banker and Chen, 2006).

Table 10 reports the estimation results for annual Fama-MacBeth (1973) cross-sectional regressions of individual firms future operating performance in year $t+1$ on lagged cost growth and other important control variables in year t over 1968–2013. We consider three measures of operating performance: profit margin (PM), return on asset (ROA), and cash flow (CF), which are important fundamental determinants of stock valuations.

The results in Table 10 indicate a negative relation between a firm's cost growth and its future operating performance changes in the next year. Specifically, Column 1 shows that the regression coefficient on cost growth for profit margin (PM) is -2.793, with a t-statistic of -4.48. In Column 2, using the return on asset (ROA) as a measure of operating performance, we find that high cost growth leads to significantly low future profitability, with a regression coefficient of -1.681 ($t = -5.04$). In Column 3, we obtain a similar relation between cost growth and future cash flow (CF), with a regression coefficient of -2.748 ($t = -8.05$). Columns 4 to 6 show that adding industry fixed effects makes no difference to the negative cost growth effect on future profitability. Overall, cost growth contains negative information about future operating performance. Firms with high cost growth appear to be less profitable in the next year in terms of profit margin, return on asset, and cash flows.

Mispricing factor

If the cost growth effect reflects market inefficiency in pricing valuation-relevant information in operating costs, we expect to observe certain degree of commonality in the mispricing, since Hirshleifer and Jiang (2010) and Hirshleifer, Hsu, and Li (2013) show that investor misperceptions and market misvaluation tend to comove across firms. We identify commonality in stock market misvaluation by using the Hirshleifer and Jiang's (2010) mispricing factor (UMO, undervalued minus overvalued), which is constructed by going long repurchase stocks and short new issue stocks.

Table 11 shows that adding the mispricing factor UMO into the Fama-French three-factor model reduces the abnormal returns of the cost growth decile portfolios substantially. The monthly average abnormal return of the cost growth long-short spread portfolios is now 0.43%, which is about 55% smaller than 0.98%, the abnormal return with the Fama-French three-factor model alone. Interestingly, the reduction in the abnormal return is mainly from the reduction of short side. More specifically, in the cross section, for the highest cost growth decile (overvalued and short side of the spread portfolio), adding the UMO factor sharply reduces the monthly abnormal return from -0.68% with the Fama-French three-factor model to -0.06 ($t = -0.37$). In contrast, the abnormal return of the low cost growth decile is generally unchanged. The UMO factor loading for the highest cost growth decile is -0.78 ($t = -11.7$), and it gradually decreases in absolute value to -0.07 ($t = -0.98$) for the lowest cost growth decile, producing a large UMO loading of 0.71 ($t = 14.52$) for the long-short cost growth spread portfolio. In summary, the cost growth spread portfolio is partially explained by Hirshleifer and Jiang's (2010) mispricing factor, although its abnormal return remains significant.

Limited attention

In this subsection, we test if the cost growth effect is driven by limited investor attention, which is motivated by recent research that limited investor attention causes market underreaction to relevant earnings information and induces mispricing (Bartov, Radhakrishnan, Krinsky 2000; Hirshleifer and Teoh 2003; Peng and Xiong 2006; Hirshleifer, Lim, and Teoh 2009).

We follow Hirshleifer and Teoh (2003) who argue that asset size and analyst coverage are proxies for investor attention, and suggest that investors with limited attention pay less attention to small firms and low analyst coverage firms. Asset size (log(AT)) is defined as the log of total assets in fiscal year ending in calendar year t. Analyst coverage (log(AC)) is defined as the log of average monthly number of analysts who provide fiscal year 1 earnings estimates in year t beginning in 1976. Asset size and analyst coverage are standardized to zero mean and unit standard deviation over the full sample period for ease of interpretation.

Panel A of Table 12 reports the Fama-MacBeth regression coefficients and t-statistics for cost growth (CG), the interaction between cost growth and asset size (CG$*$log(AT)), and the interaction between cost growth and analyst coverage (CG$*$log(AC). As expected, the negative cost growth-return relation is stronger in magnitude among firms with smaller size and lower analyst coverage. For example, the slope is 0.305 ($t = 3.67$) on the interaction of cost growth with asset size (CG$*$log(AT)), and it is 0.262 ($t = 3.06$) on the interaction of cost growth with analyst coverage (CG$*$log(AC)), both of which are economically large and statistically significant at the 1% level. This evidence appears to support the hypothesis that limited investor attention leads to the negative cost growth effect.

Valuation uncertainty

In this subsection, we test if the cost growth effect is driven by valuation uncertainty. Daniel, Hirshleifer, and Subrahmanyam (1998), Zhang (2006), and others show that investors' behavioral biases are stronger when there is higher valuation uncertainty. Recent empirical studies like Liang (2003) and Francis, LaFond, Olsson, and Schipper (2007) show that uncertainty contributes to the post-earnings announcement drift. Therefore, we expect that the negative cost growth effect is stronger among firms with higher valuation uncertainty, since investors are more likely to apply the heuristics and rule of thumb, leading to greater degree of underreaction to information embedded in cost growth.

We use idiosyncratic volatility (log(IVOL)) and firm age (log(1+Age)) as proxies of valuation uncertainty, following Kumar (2009) and Hirshleifer, Hsu, and Li (2013). Idiosyncratic volatility (log(IVOL)) is the log of standard deviation of the residuals from regressing daily stock returns on market returns over a maximum of 250 days ending on June 30 of year $t+1$. Firm age (log(1+Age)) is the log of one plus firm age defined as the number of years listed in Compustat with non-missing price data at the end of year t. Again, we standardize these uncertainty proxies to be mean mean and variance one over the full sample period.

Panel B of Table 12 reports the Fama-Macbeth regression coefficients and t-statistics for cost growth (CG), the interaction of cost growth with idiosyncratic volatility (CG*log(IVOL)), and the interaction of cost growth with firm age (CG*log(1+Age)). As expected, the coefficients on the two interactions are -0.536 ($t = -6.10$) and 0.205 ($t = 3.04$), both of which are economically large and statistically significant. Thus, the negative cost growth-return relation is stronger in magnitude among firms with higher valuation uncertainty.

Arbitrage costs

In this subsection, we test if limits to arbitrage drives the cost growth effect. Shleifer and Vishny (1997) show that mispricing can persist when arbitrage is costly and limited due to market frictions. Many recent studies provide positive evidence on the role of arbitrage costs on anomalies such as accruals (Mashruwala, Rajgopal, and Shevlin 2006) and earnings (Mendenhall 2004; Ng, Rusticus, and Verdi 2008; Chordia, Goyal, Sadka, Sadka, and Shivakumar 2009). Hence, we expect that the negative cost growth effect is stronger among firms with higher arbitrage costs, where the arbitrage opportunities driven by cost growth are more difficult to exploit and therefore less attractive to investors.

We use share price (log(PRC)), Amihud (2002) illiquidity (log(ILLIQ)), and dollar volume (log(DVOL)) as our proxies of arbitrage costs. Share price (log(PRC)) is the log of closing stock price (the average of bid and ask prices if the closing price is not available) at the end of June of year $t+1$. Stoll (2000) documents that stock price is inversely related to bid-ask spread and brokerage commission. Amihud (2002) illiquidity measure (log(ILLIQ)) is the log of the average of absolute daily return divided by daily dollar trading volume over the past 12 months ending on June 30 of year $t+1$. A higher illiquidity value indicates a larger price impact per order flow, thus a larger arbitrage costs for the investors. Dollar volume (log(DVOL)) is the log of the sum of daily share trading volume multiplied by the daily closing price from July 1 of year t to June 30 of year $t+1$. Bhushan (1994) shows that dollar volume is inversely related to price pressure and time required to fill an order or to trade a large block of shares. These three costs proxies are standardized to be zero mean and unit standard deviation over the full sample period for interpretation. Firms with lower share price, higher Amihud (2002) illiquidity measure, and lower dollar volume are interpreted as having higher arbitrage costs and hence more subject to limits to arbitrage.

Panel C of Table 12 reports the Fama-MacBeth cross-sectional regression coefficients and c t-statistics for cost growth (CG) and the interaction of cost growth with share price (CG*log(PRC)), the interaction of cost growth with Amihud (2002) illiquidity (CG*log(ILLIQ)), and the interaction of cost growth with dollar volume (log(DVOL)). The coefficient is 0.267 ($t = 3.11$) on the interaction of cost growth with share price (CG$*$log(PRC)), is -0.377 ($t = -3.25$) on the interaction of cost growth with Amihud (2002) illiquidity (CG$*$log(ILLIQ)), and is 0.282 ($t = 2.63$) on the interaction of cost growth with dollar volume (CG$*$log(DVOL)). Apparently, the negative cost growth-return relation is stronger in magnitude among firms with higher arbitrage costs. Thus, we can conclude that the limits to arbitrage appear to explain the negative cost growth effect.

V. CONCLUSION

In this paper, we show that a simple measure of cost behavior, cost growth, defined as the percentage change in annual operating costs, contains important information about a firm's fundamental value, but the market appears failing to incorporate it fully and immediately. Firms with high cost growth generate substantially lower future stock returns than those with low cost growth. A spread portfolio strategy of long low cost growth stocks and short high cost growth stocks earns an average abnormal return of 12% per year, and can add significant investment value to a diversified portfolio. This strategy is present over time and across market capitalization, and is also robust after controlling for various alternative anomalies and risks of the literature, such as size, book-to-market, momentum, liquidity, investment, profitability, and macroeconomic risks. In addition, the predictability of cost growth dominates that of sales growth in the annual horizon, and is still significant after accounting for earnings surprises and levels. In short, we contribute to the literature on understanding the cross section of stock returns by identifying a new accounting variable, cost growth, and show that it contains useful valuation information that is not well recognized by inattentive investors and is beyond the explanation of existing fundamental factors models.

We provide evidence that mispricing helps to explain the cost growth anomaly. By adding Hirshleifer and Jiang's (2010) mispricing factor into the Fama and French (1993) three-factor model, we find that the resulting four-factor model can can explain about half of the abnormal returns of the cost growth strategy. In addition, the negative cost growth-return relation is stronger among firms with lower investor attention, higher valuation uncertainty and higher arbitrage costs. These results suggest that mispricing, arising from behavioral biases and limits to arbitrage, brings about, to a large extent, the negative cost growth anomaly.

APPENDIX

Proof of the sales growth and production efficiency decomposition in Equation (3)

According to Equation (1),

$$
\begin{aligned}
\mathrm{CG}_t &= \frac{\mathrm{OC}_t - \mathrm{OC}_{t-1}}{\mathrm{OC}_{t-1}} \\
&= \mathrm{SG}_t - \Delta\mathrm{MU}_t - \mathrm{SG}_t * \Delta\mathrm{MU}_t \\
&= \frac{\mathrm{REVT}_t - \mathrm{REVT}_{t-1}}{\mathrm{REVT}_{t-1}} - \frac{\frac{\mathrm{REVT}_t}{\mathrm{OC}_t} - \frac{\mathrm{REVT}_{t-1}}{\mathrm{OC}_{t-1}}}{\frac{\mathrm{REVT}_t}{\mathrm{OC}_t}} - \frac{\mathrm{REVT}_t - \mathrm{REVT}_{t-1}}{\mathrm{REVT}_{t-1}} * \frac{\frac{\mathrm{REVT}_t}{\mathrm{OC}_t} - \frac{\mathrm{REVT}_{t-1}}{\mathrm{OC}_{t-1}}}{\frac{\mathrm{REVT}_t}{\mathrm{OC}_t}}
\end{aligned}
$$

The RHS of the above expression can be reduce to the LHS as follows:

$$
\begin{aligned}
\mathrm{RHS} &= \frac{\mathrm{REVT}_t - \mathrm{REVT}_{t-1}}{\mathrm{REVT}_{t-1}} - \frac{\frac{\mathrm{REVT}_t}{\mathrm{OC}_t} - \frac{\mathrm{REVT}_{t-1}}{\mathrm{OC}_{t-1}}}{\frac{\mathrm{REVT}_t}{\mathrm{OC}_t}} - \frac{\mathrm{REVT}_t - \mathrm{REVT}_{t-1}}{\mathrm{REVT}_{t-1}} * \frac{\frac{\mathrm{REVT}_t}{\mathrm{OC}_t} - \frac{\mathrm{REVT}_{t-1}}{\mathrm{OC}_{t-1}}}{\frac{\mathrm{REVT}_t}{\mathrm{OC}_t}} \\
&= (\frac{\mathrm{REVT}_t}{\mathrm{REVT}_{t-1}} - 1) - (1 - \frac{\frac{\mathrm{REVT}_{t-1}}{\mathrm{OC}_{t-1}}}{\frac{\mathrm{REVT}_t}{\mathrm{OC}_t}}) - (\frac{\mathrm{REVT}_t}{\mathrm{REVT}_{t-1}} - 1) * (1 - \frac{\frac{\mathrm{REVT}_{t-1}}{\mathrm{OC}_{t-1}}}{\frac{\mathrm{REVT}_t}{\mathrm{OC}_t}}) \\
&= (\frac{\mathrm{REVT}_t}{\mathrm{REVT}_{t-1}} - 1) - (1 - \frac{\frac{\mathrm{REVT}_{t-1}}{\mathrm{OC}_{t-1}}}{\frac{\mathrm{REVT}_t}{\mathrm{OC}_t}}) - (\frac{\mathrm{REVT}_t}{\mathrm{REVT}_{t-1}} - 1) + (\frac{\mathrm{REVT}_t}{\mathrm{REVT}_{t-1}} - 1) * \frac{\frac{\mathrm{REVT}_{t-1}}{\mathrm{OC}_{t-1}}}{\frac{\mathrm{REVT}_t}{\mathrm{OC}_t}} \\
&= -1 + \frac{\frac{\mathrm{REVT}_{t-1}}{\mathrm{OC}_{t-1}}}{\frac{\mathrm{REVT}_t}{\mathrm{OC}_t}} + \frac{\mathrm{REVT}_t}{\mathrm{REVT}_{t-1}} * \frac{\frac{\mathrm{REVT}_{t-1}}{\mathrm{OC}_{t-1}}}{\frac{\mathrm{REVT}_t}{\mathrm{OC}_t}} - \frac{\frac{\mathrm{REVT}_{t-1}}{\mathrm{OC}_{t-1}}}{\frac{\mathrm{REVT}_t}{\mathrm{OC}_t}} \\
&= -1 + \frac{\mathrm{REVT}_t}{\mathrm{REVT}_{t-1}} * \frac{\mathrm{REVT}_{t-1}}{\mathrm{OC}_{t-1}} * \frac{\mathrm{OC}_t}{\mathrm{REVT}_t} \\
&= -1 + \frac{\mathrm{OC}_t}{\mathrm{OC}_{t-1}} \\
&= \frac{\mathrm{OC}_t - \mathrm{OC}_{t-1}}{\mathrm{OC}_{t-1}} \\
&= \mathrm{LHS}
\end{aligned}
$$

REFERENCES

Amihud, Y., 2002. Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets* 5, 31–56.

Anderson, M.C., Banker, R.D., Janakiraman, S.N., 2003. Are selling, general, and administrative costs "sticky"? *Journal of Accounting Research* 41, 47–63.

Anderson, M.C., Banker, R.D., Huang, R., Janakiraman, S., 2007. Cost behavior and fundamental analysis of SG&A costs. *Journal of Accounting, Auditing & Finance* 22, 1–28.

Asness C., Frazzini, A., Pedersen, L., 2014. Quality minus junk. Working paper.

Balakrishnan, K., Bartov, E., Faurel, L., 2010. Post loss/profit announcement drift. *Journal of Accounting and Economics* 50, 20–41.

Ball, R., Brown, P., 1968. An empirical evaluation of accounting income numbers. *Journal of Accounting Research* 6, 159–178.

Banker, R.D., Chen, L., 2006. Predicting earnings using a model based on cost variability and cost stickiness. *The Accounting Review* 81, 285–307.

Banker, R.D., Chen, J., Park, H.U., 2014. Cost behavior models analysts and investors use. Working Paper, Temple University.

Banz, R.W., 1981. The relationship between return and market value of common stocks. *Journal of Financial Economics* 9, 3–18.

Bartov, E., Radhakrishnan, S., Krinsky, I., 2000. Investor sophistication and patterns in stock returns after earnings announcements. *The Accounting Review* 75, 43–63.

Bernard, V.L., Thomas, J.K., 1989. Post-earnings announcement drift: Delayed price response or risk premium? *Journal of Accounting Research* 27, 1–48.

Bernard, V.L., Thomas, J.K., 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economics* 13, 305–340.

Bhushan, R., 1994. An informational efficiency perspective on the post-earnings announcement drift. *Journal of Accounting and Economics* 18, 45–66.

Carhart, M.M., 1997. On persistence in mutual fund performance. *Journal of Finance* 52, 57–82.

Chen, C.X., Lu, H., Sougiannis, T., 2012. The agency problem, corporate governance, and the asymmetrical behavior of selling, general, and administrative costs. *Contemporary Accounting Research* 29, 252–282.

Chen, N.F., Roll, R., Ross, S., 1986. Economic forces and the stock market. *Journal of Business* 59, 383–403.

Chordia, T., Goyal, A., Sadka, G., Sadka, R., Shivakumar, L., 2009. Liquidity and the post earnings-announcement drift. *Financial Analysts Journal* 65, 18–32.

Chordia, T., Subrahmanyam, A., Tong, Q., 2014. Have capital market anomalies attenuated in the recet era of high liquidity and trading activity? *Journal of Accounting and Economics* 58, 41–58.

Collins, D., Hribar, P., 2000. Earnings-based and accruals-based anomalies: One effect or two? *Journal of Accounting and Economics* 29, 101–23.

Cooper, M.J., Gulen, H., Schill, M.J., 2008. Asset growth and the cross-section of stock returns. *Journal of Finance* 63, 1609–1651.

Cooper, I., Priestley, R., 2011. Real investment and risk dynamics. *Journal of Financial Economics* 101, 182–205.

DeFond, M.L., Park, C.W., 2001. The reversal of abnormal accruals and the market valuation of earnings surprises. *The Accounting Review* 76, 375–404.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under- and over-reactions. *Journal of Finance* 53, 1839–1886.

Ertimur, Y., Livnat, J., Martikainen, M. 2003. Differential market reaction to revenue and expense surprise. *Review of Accounting Studies* 8, 185–211.

Fama, E.F., French, K.R., 1993. Common risk factors in returns on stocks and bonds. *Journal of Financial Economics* 33, 3–56.

——, 1997. Industry costs of equity. *Journal of Financial Economics* 43, 153–193.

——, 2006. Profitability, investment, and average returns. *Journal of Financial Economics* 82, 491–518.

——, 2015. A five-factor asset pricing model. *Journal of Financial Economics* 116, 1–22.

Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy* 81, 607–636.

Fiske, S.T., Taylor, S.E., 1991. *Social Cognition*. 2nd edition. New York: McGraw-Hill.

Foster, G., Olsen, C., Shevlin, T., 1984. Earnings releases, anomalies, and the behavior of security returns. *The Accounting Review* 59, 574–603.

Francis, J., Lafond, R., Olsson, P., and Schipper, K., 2007. Information uncertainty and post-earnings-announcement-drift. *Journal of Business Finance & Accounting* 34, 403–433.

Garrison, R., Noreen, E., 2002. *Managerial Accounting*. 10th edition. New York, NY: McGraw-Hill.

Green, J., Hand, J.R.M., Zhang, X.F., 2013. The supraview of return predictive signals. *Review of Accounting Studies* 18, 692–730.

——, 2014. The remarkable multidimensionality in the cross-section of expected U.S. stock returns. Working Paper, Yale University.

Grinold, R.C., Kahn, R.N., 1999. *Active Portfolio Management: Quantitative Theory and Applications*. McGraw-Hill, NewYork.

Harvey, C.R., Liu, Y., Zhu, H., 2015. ...and the cross-section of expected returns. *Reiview of Financial Studies*, forthcoming.

Hirshleifer, D., Hou, K., Teoh, S.H., Zhang, Y., 2004. Do investors overvalue firms with bloated balance sheets? *Journal of Accounting and Economics* 38, 297–331.

Hirshleifer, D., Hsu, P., Li, D., 2013. Innovative efficiency and stock returns. *Journal of Financial Economics* 107, 632–654.

Hirshleifer, D., Jiang, D., 2010. A financing-based misvaluation factor and the cross-section of expected returns. *Review of Financial Studies* 23, 3401–3436.

Hirshleifer, D., Lim, S., Teoh, S.H., 2009. Driven to distraction: Extraneous events and underreaction to earnings news. *Journal of Finance* 63, 2287–2323.

Hirshleifer, D., Teoh, S.H., 2003. Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics* 36, 337–386.

Hou, K., Xue, C., Zhang, L., 2015. Digesting anomalies: An investment approach. *Review of Financial Studies* 28, 650–705.

Huberman, G., Kandel, S. 1987. Mean-variance spanning. *Journal of Finance* 42, 873–888.

Jegadeesh, N., 1991. Seasonality in stock price mean reversion: evidence from the U.S. and U.K. Journal of Finance 46, 1427–1444.

Jegadeesh, N., Livnat, J., 2006. Revenue surprises and stock returns. *Journal of Accounting and Economics* 41, 147–71.

Jegadeesh, N., Titman S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance* 48, 65–91.

Kan, R., Zhou, G. 2012. Tests of mean-variance spanning. *Annals of Economics and Finance* 13, 139–187.

Kothari, S. P., 2001. Capital markets research in accounting. *Journal of Accounting and Economics* 31, 105–231.

Kumar, A., 2009. Hard-to-value stocks, behavioral biases, and informed tranding. *Journal of Financial and Quantitative Analysis* 44, 1375–1401.

Lakonishok, J., Shleifer, A., Vishny, R., 1994. Contrarian investment, extrapolation, and risk. *Journal of Finance* 49, 1541–1578.

Liang, L., 2003. Post-earnings announcement drift and market participants' information processing biases. *Review of Accounting Studies* 8, 321–345.

Libby, R., Bloomfield, R., Nelson, M.W., 2002. Experimental research in financial accounting. *Accounting, Organizations and Society* 27, 775–810.

Lipe, R.C., 1986. The information contained in the components of earnings. *Journal of Accounting Research* 24, 37–64.

Liu, L., Zhang, L., 2008. Momentum profits, factor pricing, and macroeconomic risk. *Review of Financial Studies* 21, 2417–2448.

Livnat, J., Mendenhall, R.R., 2006. Comparing the post-earnings announcement drift for surprises calculated from analyst and time series forecasts. *Journal of Accounting Research* 44, 177–205.

Lyandres, E., Sun, L., Zhang, L., 2008. The new issue puzzle: Testing the investment-based explanation. *Review of Financial Studies* 21, 2825–2855.

Mashruwala, C., Rajgopal, S., Shevlin, T., 2006. Why is the accrual anomaly not arbitraged away? The role of idiosyncratic risk and transaction costs. *Journal of Accounting and Economics* 42, 3–33.

McLean, R.D., Pontiff, J., 2015. Does academic research destroy stock return predictability? *Journal of Finance*, forthcoming.

Mendenhall, R., 2004. Arbitrage risk and post-earnings-announcement drift. *Journal of Business* 77, 875–894.

Ng, J., Rusticus, T.O., Verdi, R.S., 2008. Implications of transaction costs for the post-earnings announcement drift. *Journal of Accounting Research* 46, 661–696.

Novy-Marx, R., 2013. The other side of value: The gross profitability premium. *Journal of Financial Economics* 108, 1–28.

Pastor, L., Stambaugh, R.F., 2003. Liquidity risk and expected stock returns. *Journal of Political Economy* 111, 642–685.

Peng, L., Xiong, W., 2006. Investor attention, overconfidence and category learning. *Journal of Financial Economics* 80, 563–602.

Penman, S., 2012. *Financial Statement Analysis and Security Valuation*, 5th edition, New York: McGraw-Hill.

Piotroski, J.D., 2000. Value investing: The use of historical financial statement information to separate winners from losers. *Journal of Accounting Research* 38, 1–41.

Qian, E.E., Hua, R.H., Sorensen, E.H., 2007. *Quantitative Equity Portfolio Management: Modern Techniques and Applications*, Chapman and Hall/CRC.

Richardson, S.A., Sloan, R.G., Soliman, M.T., Tuna, I., 2006. The implications of accounting distortions and growth for accruals and profitability. *The Accounting Review* 81, 713–743.

Shleifer, A., Vishny, R.W., 1997. The limits of arbitrage. *Journal of Finance* 52, 35–55.

Sloan, R., 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review* 71, 289–315.

Stoll, H.R., 2000. Friction. *Journal of Finance* 55, 1479–1514.

Swaminathan, S., Weintrop, J., 1991. The information content of earnings, revenues, and expenses. *Journal of Accounting Research* 29, 418–427.

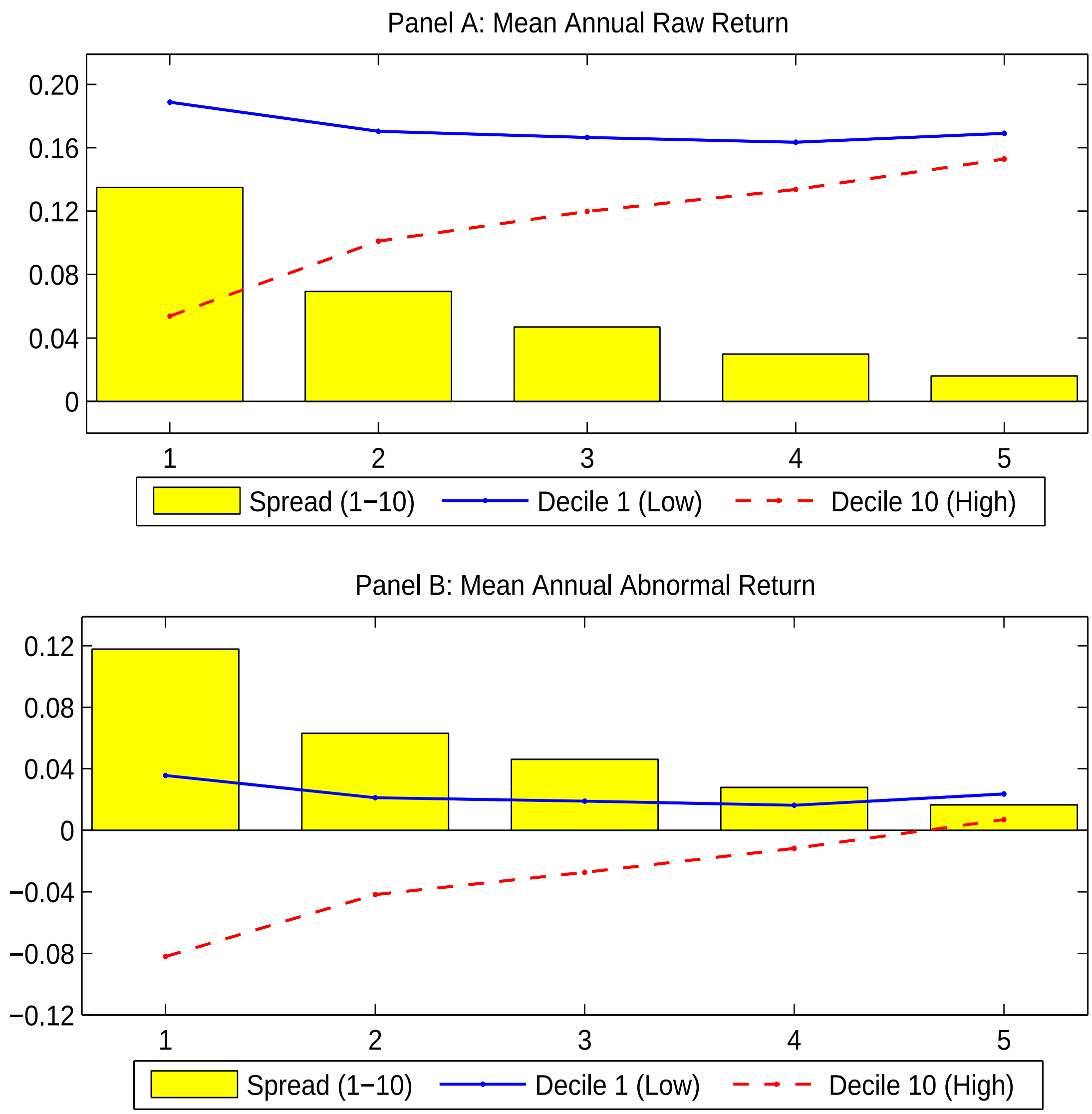
Titman, S., Wei, K.C.J., Xie, F., 2004. Capital investments and stock returns. *Journal of Financial and Quantitative Analysis* 39, 677–700.

Weiss, D., 2010. Cost behavior and analysts' earnings forecasts. *The Accounting Review* 85, 1441–1471.

Xing, Y., 2008. Interpreting the value effect through the q-theory: An empirical investigation. *Review of Financial Studies* 21, 1767–1795.

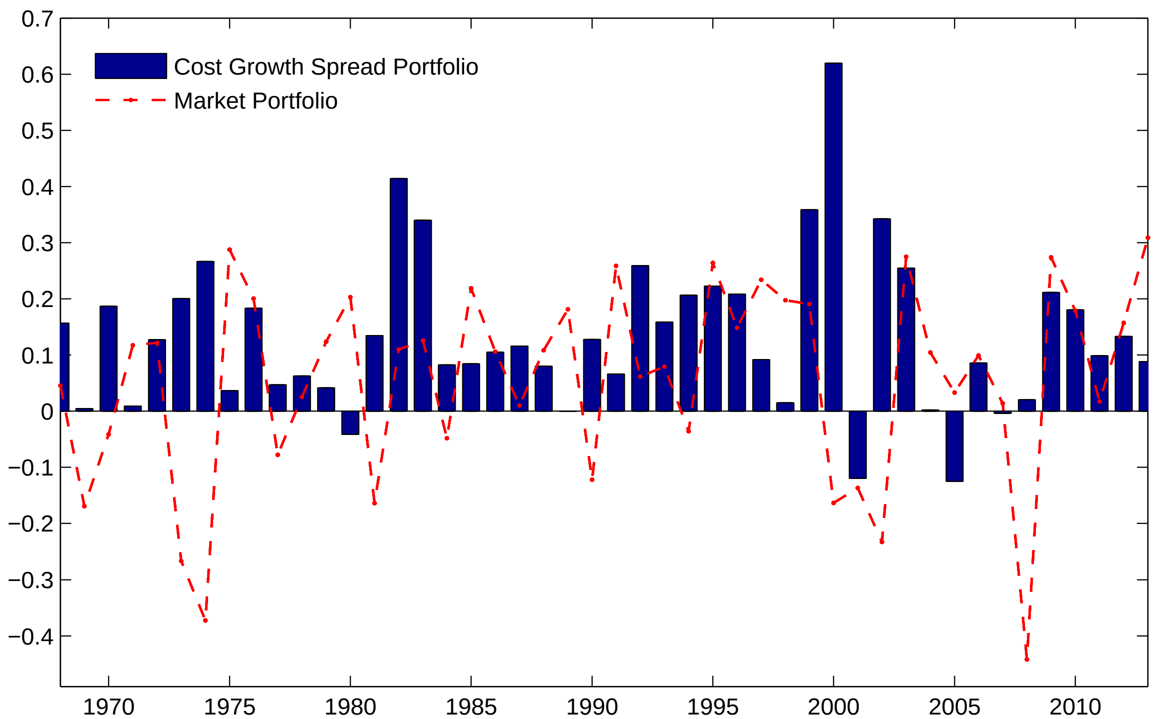
Zhang, X.F., 2006. Information uncertainty and stock returns. *Journal of Finance* 612, 105–137.

FIGURE 1
Event-time average annual raw and abnormal returns of cost growth portfolios



This figure plots the average annual returns of cost growth portfolios in the subsequent five years following portfolio formation. At the end of June of each year $t+1$, we sort firms into cost growth deciles based on cost growth rates in fiscal year ending in calendar year t. We hold these decile portfolios for five years, from July of year $t+1$ to June of year $t+6$, and compute the equal-weighted monthly returns for these portfolios. The returns of the portfolios formed in June of year $t+1$ and held from the July of year $t+1$ to June of year $t+2$ are labeled as event-year 1, and from the July of year $t+2$ to June of year $t+3$ are labeled as event-year 2, etc. Decile 1 refers to firms in the lowest cost growth decile, and decile 10 refers to firms in the highest cost growth decile. The cost growth long-short spread portfolio is computed as the difference between the returns of decile 1 and decile 10. The top graph shows the average annual raw returns of the deciles 1 and 10 and the spread portfolio, and the bottom graph shows the corresponding average annual abnormal returns, where the abnormal returns are computed as the intercepts from regressing excess portfolio returns on the Fama-French (1993) three factors. The sample period is over 1968:07–2013:12.

FIGURE 2
Time series of annual returns of cost growth spread portfolio



This figure plots the annual returns of the costs grow spread portfolio from 1968 to 2013. At the end of June of each year $t+1$, we sort firms into cost growth deciles based on cost growth rates in fiscal year ending in calendar year t. We hold these decile portfolios for one year, from July of year $t+1$ to June of year $t+2$, and compute the equal-weighted monthly returns of these portfolios. The cost growth spread portfolio is computed as the difference between the returns of the lowest and the highest cost growth deciles. We also plot the annual returns of the value-weighted CRSP market portfolio in excess of the one-month Treasury bill rate.

TABLE 1
Summary statistics

At the end of June of each year $t+1$, we sort firms into 10 cost growth deciles based on cost growth rates (CG) in fiscal year ending in calendar year t, defined as percentage changes in a firm's total operating costs (costs of goods sold (COGS) plus selling, general, and administration expenses (SGA)) from the fiscal year ending in calendar year $t-1$ to the fiscal year ending in calendar year t. "Low" refers to firms in the lowest cost growth decile, and "High" refers to firms in the highest cost growth decile. This table reports the annual average pooled contemporaneous firm characteristics and operating performance in year t of the 10 cost growth deciles from 1967 to 2013. ME is the median year-end market equity capitalization in year t. B/M is book to market ratio as defined in Fama and French (1993), where book equity is the Compustat book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit, minus book value of preferred stock (in the following order: redemption, liquidation, or par value) in fiscal year ending in calendar year t and market equity is CRSP price per share times the number of shares outstanding at the end of year t. $r_{-12,-1}$ is momentum calculated as the cumulative stock return in year t. SG is sales growth defined as the annual percentage change in sales from year $t-1$ to year t. ACC is operating accruals defined as the change in noncash current assets less the change in current liabilities excluding the change in short-term debt and the change in taxes payable minus depreciation and amortization expense deflated by average total assets. INV is investment to asset calculated as the change in gross property, plant, and equipment plus the change in inventories scaled by lagged total assets. AG is asset growth calculated as the annual percentage change in total assets. GP is gross profitability calculated as the as the annual gross profit (revenue minus costs of goods sold) scaled by total assets. PM is profit margin defined as income before extraordinary items divided by sales. ROA is return on asset defined as income before extraordinary items divided by total assets. CF is cash flow defined as net income plus amortization and depreciation minus changes in working capital and capital expenditures divided by total assets in year t. ΔPM (ΔROA, ΔCF) is the annual change in PM (ROA, CF) from year $t-1$ to year t.

Variable	Low	2	3	4	5	6	7	8	9	High
Panel A: Characteristics										
CG	-0.25	-0.06	0.00	0.04	0.08	0.12	0.18	0.25	0.39	0.96
ME	42	72	108	152	181	189	177	175	162	133
B/M	1.07	1.09	1.02	0.94	0.88	0.81	0.77	0.72	0.66	0.61
$r_{-12,-1}$	0.05	0.07	0.09	0.11	0.13	0.15	0.16	0.18	0.19	0.21
SG	-0.23	-0.06	0.00	0.04	0.08	0.12	0.17	0.25	0.39	1.08
ACC	-0.04	-0.01	0.00	0.01	0.01	0.02	0.03	0.04	0.05	0.07
INV	-0.05	0.01	0.04	0.05	0.07	0.09	0.11	0.13	0.18	0.34
AG	-0.09	0.00	0.03	0.06	0.08	0.12	0.16	0.23	0.37	0.85
Panel B: Operating performance										
GP	0.29	0.35	0.38	0.40	0.41	0.41	0.41	0.39	0.37	0.31
PM	-0.20	-0.02	0.02	0.03	0.04	0.04	0.04	0.03	-0.02	-0.23
ΔPM	0.10	0.01	0.00	0.00	0.00	0.00	0.01	0.01	-0.02	-0.29
ROA	-0.10	-0.02	0.01	0.03	0.04	0.04	0.04	0.03	0.01	-0.04
ΔROA	0.05	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	-0.05
CF	-0.10	-0.03	0.00	0.01	0.01	0.01	0.00	-0.01	-0.04	-0.11
ΔCF	0.05	0.01	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	-0.05

TABLE 2

Cost growth portfolios raw and abnormal returns and Fama-French three-factor loadings

Panel A of this table reports the monthly average raw returns (in percentage), abnormal returns (α, in percentage), factor loadings, and their t-statistics (in squared brackets) from the regressions of excess cost growth decile portfolio returns on the Fama-French (FF3, 1993) three factors over 1968:07–2013:12. At the end of June of each year $t+1$, we form decile portfolios based on cost growth (CG) in year t, defined as percentage changes in a firm's total operating costs from the fiscal year ending in calendar year $t-1$ to year t. We hold these portfolios for one year, from July of year $t+1$ to June of year $t+2$, and compute the equal-weighted monthly returns of these cost growth portfolios. "Low" refers to firms in the lowest cost growth decile, and "High" refers to firms in the highest cost growth decile. The "Low-High" spread portfolio is computed as the difference between the returns of the lowest and the highest cost growth deciles. MKT, SMB, and HML are the market, size, and value factors in Fama and French (1993). Panel B of this table reports the mispricing, α (%), with FF3 plus momentum (MOM) factor, FF3 plus Pástor and Stambaugh liquidity (LIQ) factor, FF3 plus Asness, Frazzini and Pedersen (2014) quality minus junk (QMJ) factor, Fama-French five factor (FF5, 2015), Hou, Xue, and Zhang (HXZ, 2015) four factor, and Chen, Roll, and Ross (CRR, 1986) macroeconomic factor models, respectively.

Panel A: Cost growth portfolios and FF3 pricing performance

Portfolios	Return (%)	α (%)	β_{MKT}	β_{SMB}	β_{HML}
Low	1.57 [4.88]	0.30 [2.02]	1.05 [30.9]	1.24 [25.4]	0.37 [7.14]
2	1.41 [5.25]	0.19 [1.91]	0.99 [44.1]	0.98 [30.3]	0.43 [12.5]
3	1.49 [5.99]	0.29 [3.66]	0.98 [53.2]	0.85 [32.2]	0.45 [16.0]
4	1.44 [6.11]	0.28 [4.21]	0.96 [62.6]	0.77 [34.5]	0.40 [17.1]
5	1.36 [5.79]	0.21 [3.17]	0.95 [61.9]	0.75 [33.7]	0.37 [15.7]
6	1.37 [5.72]	0.25 [3.89]	0.95 [63.9]	0.77 [35.9]	0.27 [12.0]
7	1.28 [5.11]	0.17 [2.42]	0.99 [62.0]	0.83 [36.1]	0.22 [9.01]
8	1.16 [4.27]	0.03 [0.36]	1.04 [54.6]	0.89 [32.6]	0.16 [5.47]
9	0.92 [3.13]	-0.21 [-2.27]	1.09 [50.4]	0.99 [31.6]	0.07 [2.09]
High	0.45 [1.28]	-0.68 [-4.42]	1.19 [33.3]	1.09 [21.1]	-0.11 [-2.00]
Low-High	1.12 [8.14]	0.98 [8.08]	-0.14 [-4.93]	0.16 [3.87]	0.48 [11.2]

Panel B: Abnormal returns with other factor models

Portfolios	FF3+MOM	FF3+LIQ	FF3+QMJ	FF5	HXZ	CRR
Low	0.49 [3.39]	0.29 [1.95]	0.80 [5.54]	0.47 [3.24]	0.76 [4.96]	0.96 [3.04]
2	0.33 [3.42]	0.18 [1.81]	0.38 [3.80]	0.20 [2.05]	0.42 [3.94]	0.78 [2.99]
3	0.43 [5.78]	0.29 [3.64]	0.38 [4.54]	0.29 [3.64]	0.50 [5.40]	0.86 [3.55]
4	0.39 [6.02]	0.27 [3.98]	0.25 [3.55]	0.22 [3.30]	0.39 [4.87]	0.86 [3.74]
5	0.33 [5.19]	0.20 [3.02]	0.15 [2.11]	0.16 [2.53]	0.32 [3.99]	0.67 [2.94]
6	0.37 [5.98]	0.24 [3.64]	0.23 [3.36]	0.25 [3.95]	0.40 [5.24]	0.67 [2.87]
7	0.29 [4.36]	0.16 [2.32]	0.18 [2.50]	0.18 [2.55]	0.33 [4.18]	0.63 [2.56]
8	0.21 [2.74]	0.01 [0.16]	0.13 [1.54]	0.13 [1.53]	0.30 [3.23]	0.54 [2.00]
9	0.01 [0.08]	-0.23 [-2.45]	0.04 [0.44]	0.00 [0.03]	0.26 [2.59]	0.37 [1.25]
High	-0.30 [-2.22]	-0.72 [-4.62]	-0.08 [-0.52]	-0.27 [-1.84]	0.07 [0.42]	-0.12 [-0.34]
Low-High	0.79 [6.73]	1.01 [8.25]	0.87 [6.78]	0.74 [6.40]	0.70 [5.43]	1.07 [7.63]

TABLE 3
Double sorts on cost growth and market equity

This table reports the monthly average raw returns (in percentage), monthly average abnormal returns (α, in percentage), factor loadings and their t-statistics (in squared brackets) of double sorts on cost growth and market equity from regressing excess returns of double sorts on the Fama-French (1993) three factors over 1968:07–2013:12. At the end of June of each year $t+1$, we independently sort firms into three size groups (small, middle, and large) using the 20[th] and 50[th] NYSE market equity percentiles in June of year $t+1$ and five cost growth quintiles based on cost growth rates in fiscal year ending in calendar year t as defined in Table 1. We hold these portfolios for one year, from July of year $t+1$ to June of year $t+2$, and compute the equal-weighted monthly returns of these 15 size-cost growth portfolios. "Low" refers to firms in the lowest cost growth quintile within each firm group, and "High" refers to firms in the highest cost growth quintile. The "Low-High" spread portfolio is computed as the difference between the returns of the lowest and the highest cost growth quintiles. MKT, SMB, and HML are the market, size, and value factors in Fama and French (1993).

	Return (%)	α (%)	β_{MKT}	β_{SMB}	β_{HML}
Panel A: Small size firms					
Low	1.60 [5.06]	0.35 [2.35]	0.96 [27.6]	1.31 [26.2]	0.38 [7.14]
2	1.62 [6.04]	0.42 [3.85]	0.89 [35.9]	1.11 [30.7]	0.45 [11.8]
3	1.48 [5.61]	0.30 [3.00]	0.88 [37.8]	1.10 [32.7]	0.39 [11.1]
4	1.36 [4.74]	0.18 [1.55]	0.95 [35.5]	1.15 [29.8]	0.30 [7.27]
High	0.76 [2.23]	-0.44 [-2.78]	1.06 [29.1]	1.29 [24.4]	0.13 [2.37]
Low-High	0.84 [7.98]	0.79 [8.01]	-0.11 [-4.66]	0.02 [0.71]	0.24 [7.02]
Panel B: Middle size firms					
Low	1.17 [3.98]	-0.15 [-1.61]	1.17 [55.7]	0.91 [30.0]	0.44 [13.7]
2	1.33 [5.28]	0.10 [1.51]	1.04 [70.1]	0.79 [36.8]	0.46 [20.2]
3	1.28 [5.14]	0.11 [1.52]	1.02 [63.7]	0.77 [33.2]	0.35 [14.5]
4	1.16 [4.32]	0.03 [0.42]	1.07 [71.0]	0.86 [39.6]	0.15 [6.68]
High	0.68 [2.01]	-0.46 [-3.94]	1.23 [45.6]	0.98 [25.3]	-0.12 [-3.03]
Low-High	0.49 [3.63]	0.32 [2.81]	-0.06 [-2.42]	-0.08 [-2.02]	0.56 [14.2]
Panel C: Large size firms					
Low	1.12 [4.46]	-0.05 [-0.51]	1.18 [55.9]	0.30 [9.80]	0.35 [11.0]
2	1.20 [5.39]	0.09 [1.44]	1.09 [72.9]	0.21 [9.66]	0.34 [14.8]
3	1.17 [5.33]	0.13 [2.19]	1.06 [75.0]	0.18 [8.72]	0.19 [8.79]
4	1.01 [4.14]	-0.01 [-0.11]	1.12 [72.4]	0.27 [12.2]	0.02 [0.89]
High	0.68 [2.19]	-0.32 [-2.77]	1.27 [48.3]	0.45 [11.8]	-0.29 [-7.31]
Low-High	0.44 [2.94]	0.27 [2.24]	-0.10 [-3.47]	-0.15 [-3.78]	0.65 [15.3]

TABLE 4
Fama-MacBeth regressions of stock returns on cost growth and other variables

This table reports the average slopes (in percentage) and their time series t-statistics (in parentheses) from monthly Fama-MacBeth (1973) cross-sectional regressions of monthly stock returns from July of year $t+1$ to June of year $t+2$ on lagged cost growth (CG) in fiscal year ending in calendar year t as defined in Table 1 and other accounting and return-based control variables. Size (log(ME)) is the log of market equity in June of year $t+1$. The log book to market ratio (log(B/M)) is defined and lagged as in Fama and French (1993). Momentum ($r_{-12,-2}$) is the cumulative return over the previous 12 to 2 months. Reversal (r_{-1}) is the one-month lagged return. The industry-adjusted cost growth rates and industry dummies are based on the 48 industry classification defined in Fama and French (1997). Independent variables are winsorized at the 1% and 99% levels, and the sample period is over 1968:07–2013:12.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cost growth (CG)	-0.897	-0.642	-0.665	-0.865	-0.628	-0.670	
	(-8.24)	(-6.94)	(-8.28)	(-9.47)	(-7.60)	(-8.96)	
Industry-adjusted CG							-0.660
							(-9.62)
log(ME)		-0.114	-0.113		-0.109	-0.098	-0.111
		(-2.65)	(-2.96)		(-2.67)	(-2.67)	(-2.93)
log(B/M)		0.284	0.312		0.344	0.384	0.324
		(4.50)	(5.56)		(7.10)	(8.40)	(5.64)
$r_{-12,-2}$			0.526			0.281	0.537
			(2.93)			(1.68)	(2.98)
r_{-1}			-6.347			-7.442	-6.324
			(-15.4)			(-18.7)	(-15.3)
Industry dummy				Yes	Yes	Yes	

TABLE 5
Controlling for earnings surprises and profitability

This table reports the average slopes (in percentage) and their time series t-statistics (in parentheses) from monthly Fama-MacBeth (1973) cross-sectional regressions of monthly stock returns from July of year $t+1$ to June of year $t+2$ on lagged cost growth for fiscal year ending in calendar year t and other control variables related to earnings surprises and profitability effects. $\mathrm{SUE_Q}$ is the quarterly standardized unexpected earnings computed as the most recently announced quarterly earnings minus the quarterly earnings four quarters ago standardized by its standard deviation estimated over the prior eight quarters, as a proxy for earnings surprises. $\mathrm{SUE_A}$ is the annual standardized unexpected earnings calculated as the annual earnings per share before extraordinary items (EPS) in the fiscal year ending in calendar year t minus the annual EPS one year ago standardized by the stock price per share at the end of year t. The gross profitability (GP) is calculated as the as the annual gross profit scaled by total assets. The return on asset (ROA) is calculated as the annual income before extraordinary items (IB) scaled by total assets. The return on equity (ROE) is calculated as the annual income before extraordinary items (IB) scaled by book value of equity. log(ME) is the log of market equity in June of year $t+1$. log(B/M) is the log book to market ratio defined and lagged as in Fama and French (1993). $r_{-12,-2}$ is the return from month $t-12$ to month $t-2$. r_{-1} is the one-month lagged return. Independent variables are winsorized at the 1% and 99% levels, and the sample period is over 1968:07–2013:12.

	(1)	(2)	(3)	(4)	(5)
Cost growth (CG)	-0.604	-0.666	-0.606	-0.675	-0.678
	(-3.82)	(-8.40)	(-7.52)	(-8.65)	(-8.58)
$\mathrm{SUE_Q}$	0.138				
	(5.83)				
$\mathrm{SUE_A}$		0.504			
		(2.26)			
Gross profit (GP)			0.841		
			(7.07)		
ROA				0.641	
				(1.34)	
ROE					0.141
					(0.73)
log(ME)	-0.123	-0.114	-0.102	-0.119	-0.118
	(-2.90)	(-3.01)	(-2.66)	(-3.45)	(-3.37)
log(B/M)	0.303	0.313	0.38	0.311	0.305
	(4.24)	(5.59)	(6.70)	(5.55)	(5.53)
$r_{-12,-2}$	0.186	0.516	0.477	0.503	0.512
	(0.91)	(2.90)	(2.66)	(2.86)	(2.89)
r_{-1}	-6.825	-6.379	-6.466	-6.463	-6.429
	(-13.7)	(-15.5)	(-15.7)	(-15.9)	(-15.8)

TABLE 6
Controlling for sales growth

This table reports the average slopes (in percentage) and their time series t-statistics (in parentheses) from monthly Fama-MacBeth (1973) cross-sectional regressions of monthly stock returns from July of year $t+1$ to June of year $t+2$ on lagged cost growth in fiscal year ending in calendar year t defined in Table 1 and sales growth. Sales growth (SG) reflects the growth in outputs (sales), and is defined as the annual percentage change in sales from fiscal year ending in calendar year $t-1$ to fiscal year ending in calendar year t. ΔMU reflects the change in production efficiency, is defined as the change in markup from fiscal year ending in calendar year $t-1$ to fiscal year ending in calendar year t scaled by markup in fiscal year ending in calendar year t, where markup is the sales to costs ratio. log(ME) is the log of market equity in June of year $t+1$. log(B/M) is the log book to market ratio in fiscal year ending in calendar year t defined and lagged as in Fama and French (1993) and Table 4. $r_{-12,-2}$ is the cumulative return over the previous 12 to 2 months. r_{-1} is the one-month lagged return. Independent variables are winsorized at the 1% and 99% levels, and the sample period is over 1968:07–2013:12.

	(1)	(2)	(3)	(4)
Cost growth (CG)	-0.665	-0.694	-0.661	-0.679
	(-8.28)	(-4.35)	(-7.87)	(-8.20)
Sales growth (SG)		0.031		
		(0.19)		
Change in markup (ΔMU)			0.336	
			(1.29)	
Interaction term (SG*ΔMU)				-0.456
				(-0.54)
log(ME)	-0.113	-0.113	-0.114	-0.115
	(-2.96)	(-2.99)	(-3.02)	(-3.08)
log(B/M)	0.312	0.305	0.307	0.298
	(5.56)	(5.50)	(5.51)	(5.41)
$r_{-12,-2}$	0.526	0.535	0.530	0.536
	(2.93)	(2.98)	(2.96)	(2.99)
r_{-1}	-6.347	-6.322	-6.323	-6.327
	(-15.4)	(-15.3)	(-15.3)	(-15.4)

TABLE 7
Controlling for investment and asset growth

This table reports the average slopes (in percentage) and their time series t-statistics (in parentheses) from monthly Fama-MacBeth (1973) cross-sectional regressions of monthly stock returns from July of year $t+1$ to June of year $t+2$ on lagged cost growth for fiscal year ending in calendar year t and other control variables related to investment and asset growth effects. Accruals (ACC) is the operating accruals deflated by average total assets from Sloan (1996). Net operating assets (NOA) is net operating assets (operating assets minus operating liabilities) scaled by lagged total assets from Hirshleifer, Hou, Teoh, and Zhang (2004). Investment to asset (INV) is calculated as the change in gross property, plant, and equipment plus the change in inventories scaled by lagged total assets from Lyandres, Sun, and Zhang (2008). Asset growth (AG) is calculated as the annual percentage change in total assets from Cooper, Gulen, and Schill (2008). Investment growth (IG) is calculated as the growth rate of capital expenditure from Xing (2008). Capital investment (CI) is calculated as capital expenditure divided by the average capital expenditure over the past three years from Titman, Wei, and Xie (2004), where capital expenditure is scaled by its sales. log(ME) is the log of market equity in June of year $t+1$. log(B/M) is the log book to market ratio defined and lagged as in Fama and French (1993). $r_{-12,-2}$ is is the cumulative return over the previous 12 to 2 months. r_{-1} is the one-month lagged return. Independent variables are winsorized at the 1% and 99% levels, and the sample period is over 1968:07–2013:12.

	(1)	(2)	(3)	(4)	(5)	(6)
Cost growth (CG)	-0.534	-0.421	-0.427	-0.386	-0.502	-0.571
	(-6.33)	(-5.24)	(-5.00)	(-3.39)	(-5.82)	(-6.48)
Accruals (ACC)	-1.220					
	(-5.16)					
Net operating assets (NOA)		-0.447				
		(-6.19)				
Investment to asset (INV)			-0.601			
			(-6.80)			
Asset growth (AG)				-0.552		
				(-9.28)		
Investment growth (IG)					-0.084	
					(-7.51)	
Capital investment (CI)						-0.144
						(-7.27)
log(ME)	-0.122	-0.113	-0.119	-0.111	-0.121	-0.116
	(-3.13)	(-2.95)	(-3.08)	(-2.91)	(-3.17)	(-3.05)
log(B/M)	0.317	0.325	0.313	0.280	0.290	0.262
	(5.79)	(5.63)	(5.70)	(5.10)	(5.19)	(4.56)
$r_{-12,-2}$	0.466	0.513	0.468	0.509	0.514	0.486
	(2.63)	(2.85)	(2.63)	(2.84)	(2.87)	(2.62)
r_{-1}	-6.395	-6.373	-6.372	-6.391	-6.311	-6.404
	(-15.8)	(-15.5)	(-15.7)	(-15.5)	(-15.4)	(-15.6)

TABLE 8
Alternative measures of cost growth

This table reports the average slopes (in percentage) and their time series t-statistics (in parentheses) from monthly Fama-MacBeth (1973) cross-sectional regressions of monthly stock returns from July of year $t+1$ to June of year $t+2$ on various lagged alternative definitions of cost growth in fiscal year ending in calendar year t and controls variables. CG is our main cost growth measure as defined in Table 1. $\mathrm{CG}_{\mathrm{COGS}}$ is the annual percentage changes in costs of goods sold (COGS) from the fiscal year ending in calendar year $t-1$ to the fiscal year ending in calendar year t. $\mathrm{CG}_{\mathrm{XSGA}}$ is the annual percentage changes in selling, general, and administration expenses (XSGA). $\mathrm{CG}_{\mathrm{DP}}$ is the annual percentage changes in the sum of costs of goods sold (COGS), selling, general, and administration expenses (XSGA), and depreciation and amortization expenses (DP), COGS+XSGA+DP. $\mathrm{CG}_{\mathrm{RD}}$ is the annual percentage changes in the costs of goods sold (COGS) plus selling, general, and administration expenses (XSGA) minus the R&D expenses (XRD), COGS+XSGA-XRD. $\mathrm{CG}_{\mathrm{AT}}$ is the annual change in the sume of costs of goods sold (COGS) and selling, general, and administration expenses (XSGA) scaled by lagged total assets (AT). log(ME) is the log of market equity in June of year $t+1$. log(B/M) is the log book to market ratio defined and lagged as in Fama and French (1993). $r_{-12,-2}$ is the return from month $t-12$ to month $t-2$. r_{-1} is the one-month lagged return. Independent variables are winsorized at the 1% and 99% levels, and the sample period is over 1968:07–2013:12.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cost growth (CG)	-0.665						
	(-8.28)						
$\mathrm{CG}_{\mathrm{COGS}}$		-0.446		-0.307			
		(-7.83)		(-5.37)			
$\mathrm{CG}_{\mathrm{XSGA}}$			-0.574	-0.377			
			(-7.38)	(-4.65)			
$\mathrm{CG}_{\mathrm{DP}}$					-0.597		
					(-7.67)		
$\mathrm{CG}_{\mathrm{RD}}$						-0.610	
						(-7.88)	
$\mathrm{CG}_{\mathrm{AT}}$							-0.457
							(-6.49)
log(ME)	-0.113	-0.115	-0.112	-0.113	-0.112	-0.111	-0.116
	(-2.96)	(-3.04)	(-2.96)	(-3.00)	(-2.95)	(-2.93)	(-3.04)
log(B/M)	0.312	0.317	0.322	0.303	0.316	0.322	0.322
	(5.56)	(5.60)	(5.73)	(5.43)	(5.65)	(5.70)	(5.70)
$r_{-12,-2}$	0.526	0.547	0.522	0.529	0.514	0.522	0.549
	(2.93)	(3.04)	(2.92)	(2.95)	(2.87)	(2.91)	(3.05)
r_{-1}	-6.347	-6.301	-6.354	-6.344	-6.343	-6.320	-6.339
	(-15.4)	(-15.2)	(-15.4)	(-15.4)	(-15.4)	(-15.3)	(-15.3)

TABLE 9
Mean-variance spanning tests

This table reports the results of testing whether the long-short cost growth portfolio can be spanned by various factors explored in Table 2, such as the Fama-French three factors (FF3), FF3 plus momentum (MOM) factor, FF3 plus Pástor and Stambaugh liquidity (LIQ) factor, FF3 plus Asness, Frazzini and Pedersen (2014) quality minus junk (QMJ) factor, Fama-French five factor (FF5, 2015), Hou, Xue, and Zhang (HXZ, 2015) four factor, and Chen, Roll, and Ross (CRR, 1986) macroeconomic factor models, respectively. W is the Wald test under conditional homoskedasticity, W_e is the Wald test under the i.i.d. elliptical distribution, W_a is the Wald test under the conditional heteroskedasticity, J_1 is the Bekerart-Urias test with the Errors-in-Variables (EIV) adjustment, J_2 is the Bekerart-Urias test without the EIV adjustment, and J_3 is the DeSantis test. All of the six tests have an asymptotic Chi-Squared distribution with $2N$ $(N = 1)$ degrees of freedom. The p-values are reported in the parentheses.

Model	W	W_e	W_a	J_1	J_2	J_3
FF3	70.5	41.5	64.0	33.2	31.9	35.7
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FF3+MOM	16.6	9.69	11.7	10.2	10.4	10.8
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
FF3+LIQ	71.0	41.5	70.6	42.1	40.2	40.0
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FF3+QMJ	16.8	13.2	11.8	9.93	10.4	10.3
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
FF5	10.8	10.6	11.0	10.3	10.6	10.3
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
HXZ	7.10	7.04	6.82	7.06	7.26	7.07
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
CRR	662	413	660	199	208	513
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

TABLE 10
Cost growth and subsequent operating performance

This table reports the average slopes (in percentage) and their time series t-statistics (in parentheses) from annual Fama-MacBeth (1973) cross-sectional regressions of individual firms' operating performance in year $t+1$, measured by profit margin (PM) and return on asset (ROA) and cash flow (CF), on lagged cost growth, lagged operating performance, lagged operating performance change, and a number of other control variables in year t. Profit margin (PM) is income before extraordinary items divided by sales. Return on asset (ROA) is income before extraordinary items divided by total assets. Cash flow (CF) is net income plus amortization and depreciation minus changes in working capital and capital expenditures divided by total assets. Cost growth (CG) is defined in Table 1. Lagged PM (ROA, CF) is the PM (ROA, CF) in year t. ΔPM (ΔROA, ΔCF) is the change in PM (ROA, CF) from year $t-1$ to year t. log(ME) is the log of year-end market equity. log(B/M) is the log book to market ratio defined as in Fama and French (1993). $r_{-12,-1}$ is the lagged stock return in year t. Industry dummies are based on the 48 industry classification defined in Fama and French (1997). Independent variables are winsorized at the 1% and 99% levels, and the sample period is from 1968 to 2013.

Dependent variable	PM (1)	ROA (2)	CF (3)	PM (4)	ROA (5)	CF (6)
Cost growth (CG)	-2.793	-1.681	-2.748	-2.212	-1.480	-2.432
	(-4.48)	(-5.04)	(-8.05)	(-3.78)	(-4.63)	(-7.45)
log(ME)	0.404	0.323	0.416	0.384	0.321	0.429
	(5.60)	(7.54)	(7.63)	(4.80)	(7.41)	(7.50)
log(B/M)	-0.581	-0.599	-0.117	-0.863	-0.830	-0.315
	(-2.59)	(-5.49)	(-1.58)	(-3.80)	(-6.90)	(-1.84)
$r_{-12,-1}$	2.876	2.828	1.220	2.588	2.622	1.145
	(7.88)	(10.6)	(4.53)	(9.12)	(11.5)	(4.53)
Lagged PM	74.07			71.94		
	(40.1)			(39.4)		
ΔPM	-10.32			-10.08		
	(-7.18)			(-7.11)		
Lagged ROA		71.06			69.54	
		(41.6)			(41.1)	
ΔROA		-11.69			-11.47	
		(-11.9)			(-11.8)	
Lagged CF			54.76			51.69
			(23.0)			(21.4)
ΔCF			-13.91			-13.07
			(-22.6)			(-20.9)
Industry dummy				Yes	Yes	Yes

TABLE 11
Abnormal returns and factor loadings on the Fama-French and mispricing factor model

This table reports the average monthly abnormal returns or alphas (α, in percentage), factor loadings, and their t-statistics (in square brackets) of cost growth decile portfolios from regressing excess cost growth decile portfolio returns on the Fama-French (1993) three factors augmented with the Hirshleifer and Jiang (2010) mispricing factor (UMO) over 1972:07–2013:12. MKT, SMB, and HML are the market, size, and value factors in Fama and French (1993). At the end of June of each year $t+1$, we sort firms into cost growth deciles based on cost growth rates in fiscal year ending in calendar t as defined in Table 1. We hold these portfolios for one year, from July of year $t+1$ to June of year $t+2$, and compute the equal-weighted monthly returns of these cost growth portfolios. "Low" refers to firms in the lowest cost growth decile, and "High" refers to firms in the highest cost growth decile. The "Low-High" cost growth spread portfolio is computed as the difference between the returns of the lowest and the highest cost growth deciles.

	α (%)	β_{MKT}	β_{SMB}	β_{HML}	β_{UMO}
Low	0.37 [2.22]	1.04 [26.3]	1.22 [23.2]	0.40 [5.99]	-0.07 [-0.98]
2	0.18 [1.62]	1.00 [38.0]	0.95 [27.5]	0.42 [9.54]	0.03 [0.63]
3	0.33 [3.64]	0.97 [45.4]	0.83 [29.4]	0.47 [13.1]	-0.03 [-0.67]
4	0.26 [3.45]	0.97 [54.2]	0.75 [31.9]	0.38 [12.7]	0.05 [1.45]
5	0.17 [2.30]	0.96 [53.9]	0.74 [31.4]	0.37 [12.4]	0.04 [1.13]
6	0.26 [3.56]	0.96 [55.0]	0.76 [33.2]	0.29 [9.93]	-0.01 [-0.31]
7	0.21 [2.62]	0.98 [52.8]	0.82 [33.5]	0.23 [7.54]	-0.02 [-0.67]
8	0.20 [2.15]	0.99 [45.9]	0.88 [30.8]	0.26 [7.12]	-0.18 [-4.65]
9	0.09 [0.84]	1.02 [42.6]	0.97 [30.8]	0.25 [6.24]	-0.34 [-8.03]
High	-0.06 [-0.37]	1.01 [27.3]	1.07 [21.9]	0.29 [4.75]	-0.78 [-11.7]
Low-High	0.43 [3.73]	0.03 [1.07]	0.14 [3.93]	0.10 [2.23]	0.71 [14.52]

TABLE 12
Tests of economic mechanisms: Limited attention, valuation uncertainty, and arbitrage costs

This table reports the average slopes (in percentage) and their time series t-statistics in squared brackets from monthly Fama-MacBeth (1973) regressions of stock returns from July of year $t+1$ to June of year $t+2$ on lagged cost growth in fiscal year ending in calendar year t interacted with each proxy of investor attention, valuation uncertainty, or arbitrage costs and other control variables. Cost growth (CG) is defined in Table 1. log(AT) is the log of asset size defined as total assets in fiscal year ending in calendar year t. log(AC) is the log of analyst coverage defined as the average monthly number of analysts who provide fiscal year $t+1$ earnings forecasts in year t. log(IVOL) is the log of idiosyncratic volatility defined as the standard deviation of the residuals from regressing daily stock returns on market returns over a maximus of 250 days ending on June 30 of year $t+1$. log(1+Age) is the log of one plus firm age defined as the number of years listed in Compustat with non-missing price data at the end of year t. log(PRC) is the log of share price measured as the closing stock price at the end of June of year $t+1$. log(ILLIQ) is the log of Amihud (2002) illiquidity measure defined as the average of absolute daily return divided by daily dollar trading volume over the past 12 months ending on June 30 of year $t+1$. log(DVOL) is the log of dollar trading volume defined as the sum of daily share trading volume multiplied by the daily closing price from July 1 of year t to June 30 of year $t+1$. All the proxy measures are standardized to zero mean and unit standard deviation. All the regressions also control for lagged cost growth, each individual proxy measure, log(ME), log(B/M), $r_{-12,-2}$, r_{-1}, as well as industry fixed effects with Fama and French (1997) 48 industry classification. Independent variables are winsorized at the 1% and 99% levels, and the sample period is over 1968:07–2013:12.

Panel A: Investor attention proxies

CG	CG∗log(AT)	CG∗log(AC)	Controls	Industry
-0.510 [-6.77]	0.305 [3.67]		Yes	Yes
-0.502 [-5.45]		0.262 [3.06]	Yes	Yes

Panel B: Valuation uncertainty proxies

CG	CG∗log(IVOL)	CG∗log(1+Age)	Controls	Industry
-0.622 [-8.34]	-0.536 [-6.10]		Yes	Yes
-0.535 [-7.78]		0.205 [3.04]	Yes	Yes

Panel C: Arbitrage costs proxies

CG	CG∗log(PRC)	CG∗log(ILLIQ)	CG∗log(DVOL)	Controls	Industry
-0.606 [-7.40]	0.267 [3.11]			Yes	Yes
-0.529 [-6.94]		-0.377 [-3.25]		Yes	Yes
-0.509 [-6.70]			0.282 [2.63]	Yes	Yes