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The role of firm investment in momentum and reversal[☆]

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ABSTRACT

We propose that the time delay inherent in firm investment is what creates the time delay in stock returns observed in the momentum and reversal regularities. We provide intuition for our hypothesis and show empirically that indeed the momentum and reversal effects occur not in isolation, but are concurrent with systematic patterns in firm investment. For example, winners only continue to win when there is also subsequent investment, and losers only continue to lose when there is also subsequent disinvestment. Although our paper is about understanding the nature of the price pattern delay rather than examining a trading strategy, our tests suggest ways to enhance trading returns. Our results provide novel evidence on a potential source of delay in momentum and reversals regularities.

1. Introduction

Despite a strong theoretical basis for the random-walk model of stock returns (Bachelier, 1900), evidence for predictable patterns in stock returns has mounted. Two particularly well documented patterns are the momentum and reversal effects.[1] These effects document that stocks that exhibit high (low) relative past returns tend to exhibit high (low) abnormal returns over "intermediate" horizons of 3–12 months (i.e., momentum) and low (high) abnormal returns over "long" horizons of 24–36 months (i.e., reversal). The central interesting feature of momentum and reversal is the persistent time delay in how prices evolve. If investors can anticipate momentum or reversal patterns, researchers question why competitive trading pressure does not eliminate these intermediate or long horizon effects by adjusting security prices immediately to reflect the anticipated returns. Why does the market delay in the realization of these anticipated returns? Identifying the source of this delay in equity price return adjustment remains a compelling research question.

The literature has proposed several hypotheses to explain the delay in price adjustment. Barberis et al. (1998) and Daniel et al. (1998) propose that investors maintain behavioral biases in updating their beliefs. Hong and Stein (1999) provide a model based on the interactions of investors that respond to different information to explain the price delay. Vayanos and Woolley (2013) propose a delay caused by the inertia associated with investment-fund flows.[2]

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[1] See Jegadeesh and Titman (1993, 2001), Chan et al. (1996), and Rouwenhorst (1998) for the intermediate-term momentum effect, and DeBondt and Thaler (1985, 1987), and Cutler et al. (1991) for the long-term reversal effect.

[2] There is much related work worth citing. Conrad and Kaul (1998) suggest that momentum is simply a manifestation of the cross-sectional variation in firm returns and firm risk. Chordia and Shivakumar (2002), Johnson (2002), and Sagi and Seasholes (2007) argue for rational models based on time-varying risk exposure. Grundy

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In this paper, we propose a new explanation for the time delay in returns observed in momentum and reversal. Our proposal emphasizes the role of firm investment in stock price behavior, and includes as a key feature the impact of time delay associated with realizing firm investment. We suggest that since real firm investment cannot be instantaneously executed, return patterns are delayed in time because investment realization is inherently delayed in time. Using a panel of U.S. CRSP-Compustat stocks, we show that momentum and reversal patterns in stock returns occur exclusively in concert with the predicted patterns in firm investment. For example, winners continue to win only when there is subsequent investment, and losers continue to lose only when there is subsequent disinvestment. We suggest that the momentum and reversal regularities in returns do not occur in isolation, but are dependent on systematic patterns in firm investment such that there is no residual momentum or reversal effect in stock returns independent of that associated with firm investment. While we do not empirically show causation, our results are consistent with a unique linkage between investment and both the momentum and reversal return regularities.

We motivate our proposal with two hypotheses based on simple motivating assumptions of the term-structure in returns and based on established relations. Our hypotheses result from three assertions. First, firm investment takes time to implement such that investment execution lags with some delay the manifestation of the investment opportunity. The delay in time inherent to real investment introduces uncertainty to its realization. Because of this delay the investor returns associated with the identification of an investment opportunity occur well before the investment is actually realized. A delay associated with investment is a standard assumption of neoclassical economics (see Samuelson, 1948). The delay horizon we envision is generally counted in months, not days or years. Second, firm investment is positively correlated with contemporaneous stock returns. A positive contemporaneous correlation between investment and returns is a simple implication of the realization of positive net present value projects. While investors may partially recognize the expected value associated with a project when it is identified, the realization of the uncertain portion of the value is rationally delayed until the time when the project is actualized by management. The uncertainty surrounding the realization of the investment can be attributed to a number of factors: asymmetric information between investors and the firm manager; time-varying discount rates (Cooper and Priestley, 2011); conflicting incentives, frictions, or behavioral biases within the firm (Jensen, 1986; Shleifer and Vishny, 1989; Malmendier and Tate, 2005); or behavioral biases in how investors capitalize investment (Cooper et al., 2008). Regardless of the source of the investment uncertainty, the separation of the identification of the opportunity from the execution of the opportunity divides the associated return realization of the investment into multiple parts. And third, firm investment is negatively correlated with subsequent stock returns. Empirical evidence as well as theoretical motivation on both a rational and behavioral basis for this third assertion is well established in the literature (see Carlson et al., 2004; Xing, 2008; Titman et al., 2004; Lipson et al., 2012). Combining these assertions generates the predictions of investment-based momentum and reversal effects that are at the heart of this paper.[3]

Some intuition for the investment-based momentum and reversal predictions is as follows. Because of the time delay in investment, security prices anticipate the gains to investment months before the investment occurs. Thus, positive stock returns precede investment as the returns reflect the anticipated investment opportunities. In the next period as investment is realized, security prices reflect the realized gains of the investment. This delayed return only reflects the value realized with the resolution of uncertainty that the investment is completed. It may, however, also reflect any behavioral bias in how investors capitalize firm investment (Cooper et al., 2008). This pattern in return and investment interaction generates a momentum effect as investment realization returns follow investment anticipation returns. The same is true for disinvestment. In this way, winners tend to win (as long as there is contemporaneous investment) and losers tend to lose (as long as there is contemporaneous disinvestment). Following investment, firms tend to experience lower stock returns (e.g., due to a reduction in the cost of capital that stimulated the investment or to a correction in investor pricing bias). This decline in returns is associated with the reversal pattern in stock returns as those firms that experience the positive return effect associated with the investment tend to experience lower returns following the investment. In this way firms with high pre-investment returns tend to have low post-investment returns. The opposite occurs for disinvestment. Thus, winners tend to lose over the long horizon (as long as there is contemporaneous investment) and losers tend to win over the long horizon (as long as there is contemporaneous disinvestment).

Motivated by such structure, we find that return continuation (momentum) and reversal exists only among those firms that expand following positive return shocks or contract following negative return shocks. In showing that the shape of the term structure in stock returns is inherently and jointly due to interactions between investment and returns, we propose important implications for the large literature on the momentum and reversals regularities.[4] Our explanation is holistic in that it jointly explains term-structure effects over both near-term and long-term time horizons. While our explanation does not necessarily require a rational or behavioral motivation, we provide some empirical evidence indicating that at least some of what we document has a behavioral foundation.

and Martin (2001), Jegadeesh and Titman (2001), and Griffin et al. (2003) provide contradictory evidence to these rational-based explanations. Over longer horizons investor over reaction has been used to explain the reversal effect (DeBondt and Thaler, 1985). Lo and MacKinlay (1990), Brav and Heaton (2002), and Lewellen and Shanken (2002) provide rational-based models for reversals. Klein (2001) makes the case for a tax-based explanation for which George and Hwang (2004) provide corroborating evidence.

[3] In examining the underlying assumptions of our model we find strong correlation between past returns and investment, as well as investment and contemporaneous and future returns. These findings confirm the set up of our model of the importance of investment as the channel for explaining the term-structure effects of stock returns.

[4] Recently, Novy-Marx (2012) documents that the momentum effect is stronger with more distant returns (e.g., 7 to 12 months) than more recent returns (e.g., 2 to 6 months). His observation gives rise to a complicated term structure pattern in which return correlation is increasingly positive over the intermediate term before flipping to negative correlation with the reversal effect in the long-term. Although existing models of stock returns fail to explain this curious behavior in returns, the Novy-Marx finding is fully consistent with our model as the horizon of the momentum effect depends on the delay in investment not on the common views of momentum. A delay of six to 12 months in momentum effects is completely in line with a plausible delay in investment.

Firm investment has long been known to influence firm returns.[5] While there are several papers that show interactions with momentum and investment, its role in explaining the realization of momentum and reversal in firm returns is largely unexplored. Sagi and Seasholes (2007) provide some exploratory evidence on the effect of investment on momentum effects. Liu and Zhang (2014) and Hackbarth and Johnson (2015) argue that momentum and reversal effects are consistent with the Q theory of investment. Nyberg and Poyry (2014) show a strong cross-sectional correlation between past firm investment and momentum effects. Our paper builds on their work by investigating the source of the momentum profits with an examination of subsequent investment realization as the channel by which momentum effects are realized. While Nyberg and Poyry focus on a trading strategy that sorts momentum effects based on past investment, we look at subsequent investment realization to document the channel by which winners continue to win, and vice versa for losers. We show that the time delay in momentum and reversal is fully explained by the realization of investment. The difference in purpose and setup is an important distinction between the two papers. Rather than simply focusing on the interaction, we demonstrate how the delay in momentum and reversal exist in the context of subsequent investment. That is, that neither momentum nor reversal effects exist outside of those firms that make subsequent large investment or disinvestment.

There are a number of papers that document that momentum is particularly strong among firms with particular characteristics or during particular times. We examine three of these known cross-sectional relations: share turnover, bond rating, and analyst coverage. We observe that even among stocks where past literature has shown the momentum effect to be greatest theoretically or empirically, firm investment policy provides large if not complete explanatory power. Past work has shown that in the time series, momentum effects are largest following equity market price appreciation (Cooper et al., 2004). We observe that equity market price appreciation is correlated with aggregate investment such that the known time-series effects in momentum are again conditional on aggregate investment.

We propose that total asset growth is an appropriate measure of investment for our tests. We do this in order to reflect a broad measure of firm investment. We find that total asset growth maintains greater explanatory power for momentum and reversal than two important components of total asset growth: PP&E growth and current asset growth. Lakonishok et al. (1994) document an important correlation between firm revenue growth and returns. We find that despite the strong correlation that revenue growth maintains with returns, revenue growth does not maintain the same relationship with the momentum and contrarian effects, as does investment. We document that it is investment, not revenue growth, that is required in the specification to eliminate the explanatory power of past returns on future returns. We conduct additional tests with other well-known predictive variables (operating accruals, net operating assets, and book-to-market ratio) and find that total asset investment maintains a unique role in it interaction with momentum effects.

Some of our tests suggest potentially tradable strategies in that they improve abnormal performance over naïve strategies. A reversal strategy that also sorts on investment provides substantially better abnormal returns than a naïve reversal strategy. A strategy of buying firms with low past returns and low investment and selling firms with high past returns and high investment generates an abnormal return spread of 0.76% per month. A momentum strategy that includes predicted investment as an additional sorting variable increases momentum returns for both equal- and value-weighted portfolios.[6] For example, an enhanced momentum strategy that buys stocks of the quintile with the strongest past returns and highest predicted investment and sells stocks of the quintile with the poorest past returns and lowest predicted investment generates an abnormal spread of 1.3% per month. Although the evidence of return predictability in predicted investment-based momentum is possibly inconsistent with market efficiency, it is not necessarily inconsistent with our hypotheses. The bulk of the returns associated with momentum realization are attached to the unanticipated (not anticipated) portion of investment. The monthly spread between winners with investment surprises and losers with disinvestment surprises is 3.3%, whereas the anticipated spread is 1.3%. Our hypothesis is that investment is the channel by which the momentum and reversal effects are manifest. The observation that the market may not fully efficiently price the predictable component of that subsequent investment is not central to our story, but does provide for potential trading opportunities. We also provide evidence that momentum returns are associated with aggregate investment in the time-series, in that winner less loser momentum profits are larger following periods of heavy investment.

The paper is organized with a simple motivating model in Section 2, an empirical analysis description in Sections 3 and 4, and conclusions in Section 5.

2. A simple investment-based model of momentum and reversal effects

In this section we describe a simple 3-period model of the term-structure in returns. This simple set of assertions is meant only to motivate our hypotheses of the linkage between investment and returns, not to be a full-fledged stand-alone theoretical model. The setup requires three assertions. The first assertion is that firms experience a delay between the manifestation of an investment opportunity and the execution of that opportunity. In our model, the investment delay is accomplished with distinct dates such that a positive firm return that manifests an investment opportunity in Time 0 is not acted on by the firm until Time 1. Such a delay associated with investment is a standard assumption of neoclassical economics (see Samuelson, 1948). We model this delay as a positive correlation between past returns (realized when the opportunity was identified) and future investment (realized when the opportunity was executed) as modeled in Eq. (1)

$$I_1 = a + mR_0 + u \tag{1}$$

[5] See Tobin (1969), Cochrane (1991), Berk et al. (1999), Titman et al. (2004), Cooper et al. (2008), and Liu et al. (2009) for discussions of the effect of firm investment on stock returns.

[6] Nyberg and Poyry (2014) show a closely related result—that momentum effects are correlated with past investment. Our finding is that momentum effects are correlated with predicted investment. Past investment is one important, but not comprehensive, variable in our estimate of predicted investment.

where I_1 represents the firm investment rate at Time 1 and R_0 is the firm stock return at Time 0. The positive correlation condition maintains that the coefficient m is greater than zero.

The second and third assertions are that investment is systematically associated with positive contemporaneous abnormal returns and negative subsequent returns. Motivation and evidence for these assertions are well established in the literature. A positive contemporaneous correlation between investment and returns is a simple implication of the realization of positive net present value projects. The positive return associated with the realization of the investment is independent of the return associated with the identification of the investment opportunity, as the subsequent return reflects only the realization of the uncertainty associated with the manager executing the investment. A negative correlation between investment and subsequent returns is also expected through a variety of channels. First, models of time-varying discount rates (Carlson et al., 2004; Xing, 2008) imply that declines in discount rates are associated with near-term investment as latent projects are now realized and long-term reductions in realized returns due to the reduction in required returns. Second, models of bias in investor appetite for investment growth or appreciation for the empire-building incentives of management (Titman et al., 2004; Lipson et al., 2012). The negative correlation structure between investment and subsequent returns is empirically well established (Cooper et al., 2008; Liu et al., 2009). Although these assertions are not individually novel, by combining them we propose strong testable implications of the nature of momentum and reversal returns in their linkage to investment.

The predictable return response to investment is captured with Time 1 investment being positively correlated with Time 1 returns ($n > 0$) and negatively correlated with Time 2 returns ($p < 0$). These simple relationships between investment and return are represented as follows

$$R_1 = b + nI_1 + v \tag{2}$$

$$R_2 = c + pI_1 + w. \tag{3}$$

Again, n is asserted to be a positive value in Eq. (2) representing the positive contemporaneous correlation and p is asserted to be a negative value in Eq. (3) representing the negative subsequent correlation.

The motivational basis of our paper is to simply substitute Eq. (1) into Eq. (2) to generate the following model of returns

$$R_1 = d + mn\, R_0 + x. \tag{4}$$

Since m and n are both positive, we predict a positive momentum effect as the coefficient on R_0 must be positive. We denote this relation as the investment-based return momentum hypothesis.

Investment-based Return Momentum Hypothesis. Time 1 investment is the channel through which there exists a positive correlation between Time 0 returns and Time 1 returns.

The implication of this hypothesis is that momentum in returns exists conditional and only conditional on the associated Time 1 investment. The delay in the momentum effect is explained by the delay in investment. Our hypothesis maintains that the serial correlation in returns is indirect in that it only occurs through the linkage returns have with investment. This hypothesis is based on the assumption that firm investment is uncertain. In our motivating model, this uncertainty follows from the uncertainty regarding the parameters of Eq. (1) that are not fully observable by investors. For example, with unobservable variation in parameter m, investors are unable to fully know whether the firm will realize the known investment opportunity until the investment takes place. The investment uncertainty decomposes the return realization of investment opportunities into multiple steps, as investors partially recognize the opportunity upon announcement but do not fully capitalize the value gains until the investment is realized.

To extend the model predictions into return reversals, we combine Eqs. (1) and (3). This substitution generates the following model of long-horizon returns

$$R_2 = e + mp\, R_0 + y. \tag{5}$$

Since m is positive and p is negative, we predict a reversal effect through a negative coefficient on R_0. We denote this as the investment-based return reversal hypothesis.

Investment-based Return Reversal Hypothesis. Time 1 investment is the channel through which there exists a negative correlation between Time 0 returns and Time 2 returns.

The implication of this hypothesis is that reversal in returns exists conditional and only conditional on the associated past investment.

We believe these testable implications to be strong statements. There are many possible channels whereby the momentum and reversal effects could be manifest. We claim that the key underlying feature of momentum and reversal returns is the specific association of returns with investment.

Our proposal is consistent with rational and behavioral theory of investment. As an example of a rational motivation, Berk et al. (1999) propose a model in which investment induces time variation in expected returns. In their model, time variation in the mix of firm growth options and assets in place affects realized and expected returns in a predictable way. For example, consider a firm with which an exogenous unexpected arrival of a growth option is associated with a positive return at Time 0. This positive return shock is followed by a subsequent return shock for firms that execute the valuable growth option at Time 1 (generating a momentum effect). The reduction in portfolio risk with the transformation of growth options into assets in place is associated with subsequent lower returns at Time 2 (generating a reversal effect). In such a setting, the momentum and reversal regularity are predictably consistent with an investment–return relation. See Li et al. (2009) and Liu et al. (2009) for other theory that provides intuition consistent with our evidence.

As a behavioral explanation, suppose that firm managers maintain incentives to empire build because manager compensation or perquisites are tied to firm scale (Jensen, 1986) and second, investors systematically underappreciate the empire-building incentives of managers, particularly following positive shocks to returns such as that proposed by Titman et al. (2004).[7] Based on these two premises, an investment-based momentum and reversal pattern emerges in the following manner. Suppose a firm experiences a positive exogenous return shock. This shock facilitates asset expansion as the positive wealth effects facilitate empire-building management to maximize their own utility. Investors respond to the asset expansion by initially bidding up firm stock as investments are undertaken but later bidding down the securities as the magnitude of non-value creating empire building is revealed.[8]

The associated pattern is thus that high returns are followed with some delay by high returns (as managers invest for either empire building or value creating investment realization objectives) and later by low returns (as equilibrium returns decline or the empire-building nature of the investment is revealed). The same is true of poor returns as poor returns are associated with subsequent poor returns and later followed by high returns. Moreover, an investment-based explanation is fully consistent with the challenging Novy-Marx (2012) delayed structure of momentum due to the friction in time associated with firm investment in that momentum effects are delayed by investment.

3. Cross-sectional regression tests

3.1. Data characteristics

We use the sample of all U.S. CRSP-Compustat non-financial firms over the period from 1976 to 2011. Compustat starts reporting quarterly data across a wide sample of firms at the end of 1974. The 1976 start date allows us to include enough variable lags in the regression analyses. Since six-month sorting horizons are commonly used in the momentum literature we use a "half-year" timing convention in much of the study. There are some constraints on the frequency with which financial statements are updated due to frequency of balance sheet reporting required in the United States. In order to obtain half-year balance sheet data we use the Compustat quarterly files to compute a 6-month investment rate each quarter. We denote the half-year +1 as the holding period half-year in our tests. Half-year −1 is the six-month period before the holding period and half-year -2 is the six-month period before the −1 period. We follow a similar reference point for other horizons. We define quarters as the calendar quarter corresponding to the date of the quarterly statement, to align the quarters across firms, and account for fiscal year ends other than December. We choose the comprehensive measure of total investment as captured by the total asset growth rate as our measure of business investment. This measure suggests that firms that make any investment in the assets of their business, whether it be accounts receivable, inventory, intangible assets, or PP&E, are presumably making a conscious choice to put investor capital to some worthy purpose. The total asset growth measure of investment has been shown to provide the most explanatory power for subsequent firm return effects (Cooper et al., 2008; Lipson et al., 2012). This measure is obtained as simply the sum of the quarterly percentage growth in total assets for two consecutive quarters (Compustat Data Item 'ATQ'). Empirically we also find that this measure is important in that the results documented in this paper are stronger than several other standard measures of investment.[9]

Table 1 provides summary statistics for the stock return and firm investment figures for our sample. The stock return data is from CRSP. Our sample includes nearly two hundred thousand firm-half-year observations where the half-year is measured from January to June and from July to December. The mean value for the cumulative half-year gross return is 6.2% (standard deviation of 31%) and for investment rate is 3.7% (standard deviation of 16%). We also report the serial correlation structure for these two measures. For the returns we observe a correlation coefficient of 0.053 at a lag of one half-year, diminishing to 0.019 for a lag of two half-years, shifting to a negative value of −0.039 at a lag of three half-years, and then to −0.001 at a lag length of four half-years. These values suggest that across the term structure of returns in our sample, there exists a return continuation at near-term lengths and a return reversal effect at longer lengths.

To appreciate the relation between momentum effects and asset growth rates, we report summary statistics for the associated investment rates over the same holding period as the returns. For firm investment we observe a correlation coefficient of 0.053 at a lag of one half-year (precisely the same magnitude as that observed for returns), increasing to 0.182 for a lag of two half-years, declining to 0.009 at a lag of three half-years, and then back to 0.123 at a lag length of four half-years. The oscillating correlation structure suggests some seasonality in investment.

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[7] We define empire building as asset expansion that may or may not be associated with economic gains for investors. The observation that abnormal investment is followed by return reversal is not completely new. An expanding body of research explores the asset pricing implications of changes in firm asset levels. Variously referred to as an "investment effect" and tied to capital investment activity or an "asset growth effect" and tied more broadly to changes in total assets, the underlying empirical regularity is a negative correlation between growth in assets and subsequent returns. Representative papers include Fairfield et al. (2003), Titman et al. (2004), Broussard et al. (2005), Anderson and Garcia-Feijoo (2006), Lyanders et al. (2008), Xing (2008), Cooper et al. (2008), and Polk and Sapienza (2009).

[8] Another behavioral explanation is based on bias in expectations by managers and investors as firms tend to overinvest following positive firm returns and over disinvest following negative firm returns. In both of these explanations, the patterns of momentum and reversal are only found to exist in the context of the related investment policy.

[9] Other measures we consider include the Lyandres et al. (2008) measure, the Polk and Sapienza (2009) measure, and a decomposition of the total asset growth measure. The Lyandres, Sun, and Zhang is defined as the change in inventory and gross PP&E divided by lagged assets. The Polk and Sapienza measure is defined as capital expenditures divided by net property, plant, and equipment.

Table 1
Summary statistics.

	Gross stock returns (Ret)	Investment rate (Inv)
Number of firm half-years	191,781	189,043
Mean	0.0619	0.0371
Std. deviation	0.3057	0.1623
Serial correlation of lag		
−1	0.0533	0.0525
−2	0.0187	0.1823
−3	−0.0391	0.0088
−4	−0.0011	0.1231

This table reports summary statistics for gross stock returns and investment rates for a sample that includes all U.S. CRSP-Compustat firms from 1976 to 2011. The holding period for both returns and investment rates is on a non-overlapping half-year basis, where the half-year is measured from January to June and from July to December. The investment rate (Inv) is defined as the natural logarithm of 1 plus the six-month growth in total assets from the quarterly Compustat file. The gross stock return (Ret) is the cumulative 6-month total return for the firm from CRSP. The mean investment rate is the time-series mean of the cross-section median investment rate. The mean of gross returns is the mean of the mean in gross returns. Standard deviation and serial correlation coefficients are the time-series mean of the cross-sectional standard deviation and serial correlation.

3.2. Modeling investment

To examine the evidence for our model's first assertion that investment is positively correlated with past returns, we estimate an empirical model of investment. We run Fama–MacBeth cross-sectional regressions each non-overlapping half-year. Again, our half-year timing convention is motivated by the momentum literature. The mean coefficient estimates for the time-series of cross-sectional regressions are reported in Table 2. In these tests, we regress firm investment rates for half-year +1 on a number of firm variables that we expect explain investment. We include the prior investment rates for the firm for half-years −1, −2, −3, and −4. LogAssets is defined as the natural logarithm of the total assets of the firm at the end of the previous half-year (−1). The book-to-market ratio is defined following the same dating scheme. We include industry dummy variables, defined at the 2-digit SIC code level to capture fixed effects in investment. To control for outlier effects in the regression, the variables (except for returns) are log transformed and all variables are winsorized at the 0.5% and 99.5% levels. Because the investment rate can take non-positive values, we add one to this variable before taking the log. The standard errors are adjusted for serial correlation.

We observe a significant negative coefficient on the size variable and book-to-market ratio. These signs suggest, not surprisingly, that small, glamor firms tend to invest proportionally more than large, value firms. The signs on the lagged investment rates suggest that investment rates with lags of one and two years maintain the most explanatory power (half years −2 and −4). The coefficients on the intervening half-years maintain no effect (lag −1) to a significant negative sign (lag −3). This is consistent with the seasonal time-series pattern in investment observed in Table 1.

In the second specification (Regression 2), we omit the past investment rates and add the past half-year stock return values. We observe very strong positive association between firm returns and firm investment. The *t*-statistics with the stock returns are 14.9, 16.2, 17.1, and 12.3 for returns with lags −1, −2, −3, −4, respectively. The positive coefficients are consistent with the positive correlation assertion in Eq. (1) of our model. The mean *r*-squared value for Regressions 1 and 2 indicate that the four lagged return measures maintain a slightly greater explanatory power in predicting investment than do the four lagged investment rates.

Overall the tests suggest strong evidence for a positive correlation between investment and past returns. In Specification 3 we combine both investment rates and stock returns as regressors. We observe that the stock returns maintain their importance in explaining the cross-section of firm investment rates: firms with strong past stock returns maintain substantially higher asset growth rates. The one coefficient that substantially changes is that on the single lag investment rate. The coefficient on Inv(−1) declines from 0.001 (*t*-stat = 0.25) to −0.042 (*t*-stat = −8.07). These changes in sign are suggestive of the interrelations we document in this paper. It is particularly interesting to note that in explaining investment, past returns maintain a greater explanatory power than do past investment (as evidenced by the higher *t*-statistics on past returns). Specifically, past returns are highly correlated with high investment rates. This relation motivates the role investment might play in the momentum and reversal effects.

In specification 4 we include two additional control variables: a measure of capital intensity (revenue for the past two quarters divided by assets) with a half-year lag and a measure of cash flow or profitability of investment (ROA, the sum of operating profit before depreciation for the past two quarters divided by assets). We include these variables because they have been shown to predict investment in past work (see Fazzari et al., 1988). Because of multicolinearity in the regressors the standard errors increase and the *t*-statistics drop in this specification. Nevertheless, the explanatory power of this regression is improved. With the additional regressors, past stock returns continue to maintain significant positive explanatory power in explaining investment, consistent with our assertion.

Table 2
Investment regressions.

	(1)	(2)	(3)	(4)
Inv(−1)	0.001		−0.042***	−0.037***
	(0.25)		(−8.07)	(−4.03)
Inv(−2)	0.122***		0.105***	0.088***
	(10.99)		(9.60)	(4.73)
Inv(−3)	−0.018***		−0.010*	−0.027*
	(−2.93)		(−1.72)	(−1.73)
Inv(−4)	0.061***		0.081***	0.096***
	(6.90)		(8.52)	(5.04)
Ret(−1)		0.075***	0.080***	0.068***
		(14.87)	(15.79)	(9.35)
Ret(−2)		0.045***	0.047***	0.049***
		(16.15)	(15.97)	(5.52)
Ret(−3)		0.031***	0.028***	0.025***
		(17.13)	(15.74)	(8.00)
Ret(−4)		0.030***	0.023***	0.021***
		(12.29)	(9.11)	(5.18)
Capital intensity				0.020***
				(5.23)
ROA				0.187***
				(9.12)
LogAssets	−0.004***	−0.003***	−0.003***	−0.004***
	(−6.07)	(−4.59)	(−4.21)	(−6.09)
Book-to-market ratio	−0.041***	−0.029***	−0.025***	−0.019***
	(−18.12)	(−18.99)	(−16.67)	(−5.75)
Intercept	0.023***	0.021***	0.016**	0.013
	(3.41)	(2.66)	(2.10)	(1.59)
2-digit SIC dummies	Yes	Yes	Yes	Yes
Mean *R*-squared	0.141	0.142	0.175	0.203

This table reports regression results for investment rates for a sample that includes all U.S. CRSP-Compustat firms from 1976 to 2011. We report Fama–MacBeth equal-weighted cross-sectional regression results with the investment rates as the dependent variable. We run non-overlapping regressions every six months. The measurement period for the investment rates is on a non-overlapping half-year basis, where the half-year is measured from January to June and from July to December. The investment rate is defined as the six-month growth in total assets from the quarterly Compustat file. In these regressions, we include as regressors: past investment rates and past gross stock returns—the cumulative 6-month total return for the firm from CRSP. We also include the following: LogAssets which is defined as the natural logarithm of the total assets of the firm and the book-to-market ratio, both variables measured as of the end of the fiscal quarter before we measure the dependent variable. All regressions include industry dummies, and the last regression includes two additional control variables: lagged values of firm return on assets and capital intensity. Return on assets is the sum of the previous two consecutive ratios of operating income before depreciation for the quarter divided by assets, and capital intensity is the average of the two consecutive sales for the quarter divided by assets. The variable timings vary, and we include in parentheses the timings in relation to the dependent variable in half-years, such that −1 is the half-year before the dependent variable and +1 is the half-year contemporaneous to the dependent variable. To control for outlier effects in the regression, all variables (except returns) are log transformed and all variables are winsorized at the 0.5% and 99.5% levels. Because the asset growth rate can take non-positive values, we add one to this variable before taking the log. The standard errors are adjusted for serial correlation, and *** denote significance at the 1% level, ** at the 5% level and * at the 10% level.

3.3. Modeling returns

The Fama–MacBeth set up can also be used to document the momentum and reversal effect. We use monthly gross returns as the dependent variable and define our lagged return variables in the following way. The variable "Past Month Return" is defined as the monthly gross return for the prior month. The variable "Ret(−1)" is defined as the cumulative return for months −2 to −6 prior to the formation of the dependent variable. The variable "Ret(−2)" is defined as the cumulative return for months −7 to −12 prior to the formation of the dependent variable. Book-to-market ratio and market cap, defined as the market value of equity divided by 1000, are measured as of the end of the quarter, and at the end of the month before we measure the dependent variable, respectively. Inv(t) is the 6-month growth in assets for time t. The timing −1 refers to the 6-month investment rate as of the quarter before we measure the dependent variable. To control for outlier effects in the regression, all variables except returns are log transformed and all independent variables are winsorized at the 0.5% and 99.5% levels and the standard errors are adjusted for serial correlation.[10]

[10] We recognize that some of our control variables may not yet be publicly available by the beginning of the holding period associated with our dependent variable. Our decision to not lag these variables further is based on our desire to conduct our analysis in the absence of any concern that the control variables are "stale". The results are similar, however, if lagged control variables are used.

Table 3
Regression estimates of momentum effects.

Panel A. Continuous variables				
	Unweighted		Weighted	
	(1)	(2)	(3)	(4)
Ret(−1)	0.006*	−0.004	0.005	−0.007
	(1.74)	(−1.03)	(1.23)	(−1.53)
Ret(−2)	0.007***	0.002	0.007**	0.004
	(2.73)	(0.73)	(2.52)	(1.06)
Inv(+1)		0.081***		0.050***
		(23.36)		(14.88)
Inv(−1)		0.019***		0.009**
		(6.54)		(2.53)
Inv(−2)		−0.017***		−0.010***
		(−9.19)		(−3.26)
Inv(−3)		−0.012***		−0.010***
		(−6.47)		(−3.93)
Inv(−4)		−0.009***		−0.007**
		(−4.70)		(−2.51)
Past Month Return	−0.039***	−0.057***	−0.035***	−0.034***
	(−6.75)	(−10.02)	(−6.02)	(−4.65)
Book-to-market ratio	0.005***	0.007***	0.004***	0.003***
	(4.77)	(7.65)	(4.23)	(2.70)
Market cap	0.000	0.000	0.000	0.000
	(0.09)	(0.42)	(0.21)	(0.88)
Intercept	0.010**	0.008*	0.009*	0.005
	(2.10)	(1.79)	(1.82)	(0.95)
Mean R-squared	0.046	0.068	0.052	0.133

Panel B. Indicator variables					
	Unweighted			Weighted	
	(1)	(2)	(3)	(4)	(5)
D(Ret(−1) = High)	0.006***	0.003**	0.002	0.005***	−0.002
	(4.89)	(2.04)	(1.39)	(3.99)	(−0.83)
D(Ret(−1) = Low)	−0.006***	−0.002	−0.001	−0.005***	0.002
	(−3.36)	(−1.11)	(−0.48)	(−3.06)	(1.11)
D(Ret(−2) = High)	0.004***	0.002	0.000	0.004***	0.000
	(3.02)	(1.53)	(0.18)	(2.75)	(0.09)
D(Ret(−2) = Low)	−0.005***	−0.003**	−0.002	−0.005***	−0.000
	(−3.24)	(−2.15)	(−1.18)	(−3.11)	(−0.26)
D(Inv(+1) = High)		0.019***	0.016***		0.007***
		(14.24)	(13.76)		(6.84)
D(Inv(+1) = Low)		−0.019***	−0.016***		−0.009***
		(−14.4)	(−13.96)		(−7.66)
D(Ret(−1) = High) × D(Inv(+1) = High)			0.009***		0.011***
			(5.83)		(4.58)
D(Ret(−1) = Low) × D(Inv(+1) = Low)			−0.007***		−0.012***
			(−4.57)		(−5.07)
D(Ret(−2) = High) × D(Inv(+1) = High)			0.007***		0.009***

(*continued on next page*)

In our first regression specification, we regress firm returns on the size of the firm's equity capitalization, the book-to-market ratio, the past month return, and the past firm returns of lags one and two. Results are reported in panel A of Table 3. In an equal-weighted set up, we observe a positive correlation for book-to-market ratio and a negative correlation with past month return as expected. We also note a positive association with the past return of lag one and an even stronger association with past returns from months

Table 3 (*continued*)

Panel B. Indicator variables

	Unweighted			Weighted	
	(1)	(2)	(3)	(4)	(5)
			(4.94)		(4.16)
D(Ret(−2) = Low) × *D*(Inv(+1) = Low)			−0.005***		−0.006**
			(−3.94)		(−2.58)
Past Month Return	−0.039***	−0.005***	−0.052***	−0.034***	−0.030***
	(−6.72)	(−5.33)	(−9.21)	(−5.96)	(−3.91)
Book-to-market ratio	0.005***	−0.000	0.007***	0.004***	0.003***
	(4.30)	(−0.82)	(7.30)	(3.80)	(2.88)
Market cap	−0.000	−0.055***	−0.000	−0.000	0.000
	(−0.38)	(−9.88)	(−0.22)	(−0.23)	(0.83)
Intercept	0.013***	0.016**	0.013***	0.012***	0.007
	(2.98)	(2.34)	(3.04)	(2.63)	(1.32)
Mean *R*-squared	0.047	0.06	0.064	0.049	0.066

Panel C. Forms of investment

		Definition of investment (InvX)		
	Main effects	Total assets	PPE	Current assets
D(Ret(−1) = High)	0.001			
	(0.90)			
D(Ret(−1) = Low)	0.000			
	(0.29)			
D(Ret(−2) = High)	−0.000			
	(−0.24)			
D(Ret(−2) = Low)	−0.001			
	(−0.38)			
D(InvX(+1) = High)		0.015***	−0.003***	0.003***
		(11.90)	(−3.53)	(4.47)
D(InvX(+1) = Low)		−0.013***	−0.003***	−0.004***
		(−12.02)	(−4.16)	(−5.32)
D(Ret(−1) = High) × *D*(InvX(+1) = High)		0.007***	−0.001	0.005***
		(4.02)	(−0.71)	(3.16)
D(Ret(−1) = Low) × *D*(InvX(+1) = Low)		−0.004**	−0.004**	−0.003
		(−2.34)	(−1.99)	(−1.48)
D(Ret(−2) = High) × *D*(InvX(+1) = High)		0.006***	0.001	0.001
		(4.33)	(0.56)	(0.64)
D(Ret(−2) = Low) × *D*(InvX(+1) = Low)		−0.004***	−0.002*	−0.002
		(−2.61)	(−1.65)	(−1.18)
Past Month Return	−0.054***			
	(−9.44)			
Book-to-market ratio	0.008***			

(*continued on next page*)

−7 to −12 (half-year −2). In documenting the well-known momentum effect in stock returns, we observe results consistent with Novy-Marx (2012) as the coefficient on lag −1 of 0.006 (t-stat = 1.74) is smaller than that associated with lag −2 of 0.007 (t-stat = 2.73). As argued by Novy-Marx, this finding of stronger correlation with more dated returns is inconsistent with the traditional view of momentum being driven by a continuation of winners continuing to win and losers continuing to lose. We test an alternative explanation.

We now turn to tests of our second assertion. In Specification 2 of Panel A, we add contemporaneous and lagged investment rates as regressors. We observe strong association between firm returns and firm investment. The t-statistics with the past investment are large at 6.54, −9.19, −6.47, and −4.70 for investment with lag −1, −2, −3, −4, respectively. The negative coefficients are consistent with Eq. (3) and existing literature (see Titman et al., 2004; Cooper et al., 2008; Liu et al., 2009). We also observe a particularly strong correlation with contemporaneous investment. The coefficient on Inv(+1) is 0.081 (t-stat = 23.36). Clearly, firms that invest tend to contemporaneously generate high returns. There is strong empirical support for both assertions of the model.

Table 3 (*continued*)

Panel C. Forms of investment

	Main effects	Definition of investment (InvX) Total assets	PPE	Current assets
	(7.62)			
Market cap	−0.000 (−0.15)			
Intercept	0.014*** (3.35)			
Mean R-squared	0.073			

This table reports regression estimates for gross stock returns. The Fama–MacBeth regressions are estimated monthly, and we report the average of these coefficients. The dependent variable is the monthly total return for the firm from CRSP. Regarding the independent variables, the measurement period for both returns and growth rates is on a half-year basis. The investment rate (Inv) is defined as the six-month growth in total assets from the quarterly Compustat file. Market cap is defined as the market value of equity as of the month before we measure the dependent variable divided by 1000. The book-to-market ratio is as of the fiscal quarter before we measure the dependent variable. To control for outlier effects in the regression, all continuous variables except returns are log transformed, and all independent variables are winsorized at the 0.5% and 99.5% levels. Because the asset growth rate can take non-positive values, we add one to this variable before taking the log. The Past Month Return is defined as the monthly return for the month prior to the month we measure the dependent variable. The variable timings vary, and we include in parentheses the timings in relation to the dependent variable in half-years, such that −1 is the half-year before the dependent variable and +1 is the half-year contemporaneous to the dependent variable. A slight adjustment is made for Ret(−1) to exclude Past Month Return so that Ret(−1) is defined as cumulative gross return for months −6 to −2. Equal-weighted regressions are denoted "unweighted," whereas in "weighted" regressions the observations are weighted by the natural logarithm of the stock's market capitalization. In Panel B we include various dummy variables indicating the top and bottom quintiles of asset growth and returns. In Panel C we report the coefficients for a single regression. Regarding the independent variables, each column in Panel C represents a different measure of investment, and is indicated in the column heading. Each measure of investment enters the regression as a main effect, and interacted with the different return variables. The various forms of investment are based on total assets, property, plant, and equipment (PPE), and non-cash current assets, and are defined as the six-month change in the component scaled by total assets from the quarterly Compustat file. The standard errors are adjusted for serial correlation, and *** denote significance at the 1% level, ** at the 5% level and * at the 10% level.

With the investment rate values included, we observe that the coefficient on the contemporaneous investment rate (+1) is high and positive, consistent with the second assertion of the model in Eq. (2). Controlling for investment in the return regression, we find a striking effect on momentum as the coefficient on Ret(−1) drops from 0.006 (t-stat = 1.74) to a coefficient with a different sign −0.004 (t-stat = −1.03). The coefficient on Ret(−2) drops from 0.007 (t-stat = 2.73) to 0.002 (t-stat = 0.73). With the coefficients on past returns moving from statistically significant to statistically insignificant the tests indicate that momentum is dependent on the prevailing firm investment policy. In fact, our evidence suggests that the inclusion of past and contemporaneous investment rates subsumes the explanatory power of past returns. The evidence is consistent with the view proposed in the model that past returns maintain no predictive power outside of the correlation associated with investment rates.

There is some evidence that the momentum effect is relatively strong among large cap firms (Fama and French, 2008). In the remaining specifications we weight the firm observations by the natural logarithm of firm market capitalization. In Specification 3 we do observe that the coefficients on past returns remain large for our value-weighed specification. We also observe that the Novy-Marx result holds in our weighted regression set up. The coefficient on Ret(−2) maintains greater explanatory power than Ret(−1) and the t-statistic is equal to 2.52. When we include the firm investment policy values, we again see that the explanatory power of past return evaporates (Specification 4). The results portrayed in Table 3 illustrate a substantial association between contemporaneous and previous stock returns and contemporaneous and previous investment rates.

The existing literature indicates that the correlation structure is accentuated with the magnitude of past performance in that the serial correlation is higher for winners (firms with strong past performance) and losers (firms with weak past performance). Panel B accommodates a non-linear structure in predictive power by identifying winners and losers with indicator variables. In the table we report estimates of cross-sectional regressions similar to those in Panel A but with strong past performance indicated with a variable D(Ret(−1) = High) that indicates that the firm stock return was among the top 20 percent of all firms in the sample in half-year −1 (months −2–−6) and variable D(Ret(−1) = Low) that indicates that the firm stock return was among the bottom 20 percent of all firms in the sample in half-year −1 (months −2–−6). We also include indicator variables for strong and poor past performance for half year −2, which we define in identical fashion. Regression 1 shows the mean coefficients estimates in a specification that includes the two past return indicators and the following control variables: size, book-to-market ratio, and past month return. The estimates show a strong momentum effect with coefficients of 0.006 (t-stat = 4.89) for D(Ret(−1) = High) and −0.006 (t-stat = −3.36) for D(Ret(−1) = Low). The coefficients are similar for returns in half-year −2. The regressions shows strong evidence that winners tend to continue to win in the near term and losers tend to continue to lose in the near term.

In Regression 2, two regressors are added: indicator variables D(Inv(+1) = High) to indicate top 20 percentile investment rates in half-year +1 and D(Inv(+1) = Low) to indicate bottom 20 percentile investment rates in half-year +1. The coefficients on these variables are highly significant. Top 20th percentile investment is associated with strong positive returns and bottom 20th percentile investment is associated with strong negative returns. The inclusion of these investment variables reduces but does not eliminate the explanatory power of past returns as it did with the continuous measures in Panel A. In Regression 3 we interact the investment indicators with the past return variables. We find these interaction effects to be important. Firms with past high returns and high subsequent investment are associated with large subsequent returns while the opposite is true for firms with poor returns and low investment. The coefficients suggest strong serial correlation for winner firms that subsequently invest and for loser firms that subsequently disinvest. The inclusion of these interactions eliminates the statistical significance of the past return variables in isolation. The coefficients on the past returns variables are no longer significantly different from zero at the conventional levels, with a value of 0.002 (t-stat = 1.39) for $D(\text{Ret}(-1) = \text{High})$, −0.001 ($t$-stat = −0.48) for $D(\text{Ret}(-1) = \text{Low})$, 0.000 ($t$-stat = 0.18) for $D(\text{Ret}(-2) = \text{High})$, and −0.002 ($t$-stat = −1.18) for $D(\text{Ret}(-2) = \text{Low})$. We repeat this exercise with weighted regressions, and again find a similar effect. The regression estimates indicate that the tendency for winners to continue to win is isolated to be among only those winners that subsequently are among the firms with the highest investment rates. Moreover, the tendency for losers to continue to lose is isolated to be among only those losers that subsequently are among the firms with the lowest investment rates.

In this study we have selected total asset growth as the measure of investment. This choice is arguably ad hoc. To investigate the merits of alternative definitions and sub-categories of firm assets, we use the quarterly data to calculate the half-year growth in property, plant, and equipment (PPE) and in non-cash current assets in the same manner as we calculated total asset growth. Specifically, we sum, for two consecutive quarters, the quarterly change in the respective asset group scaled by total assets. The Compustat codes for these variables are PPENTQ for PPE and ACTQ minus CHEQ for non-cash current assets. We then estimate an alternative specification to Regression 3 of Panel B. In this regression we add the high and low indicator variables for two alternative measures of investment: PPE growth and current asset growth. We also interact these two investment rates with the return indicators as in Regression 3. We report the coefficients of this single regression in Panel C of Table 3. We observe that the inclusion of the alternative definitions of investment, total asset investment remains as providing the dominant explanatory power with respect to returns. While the interaction variables are important with all four interaction specifications for total asset investment, the same cannot be said of PPE growth and current asset growth. The interaction terms for PPE growth are significantly different from zero with only the stocks specified as losers, and then only weakly so. The interaction terms for current asset growth are significantly different from zero with only the most recent stocks specified as winners. Overall the test provides some support of the selection of total asset growth as the measure of investment as it dominates the other component measures. We consider two additional measures of investment: growth in PPE and inventory scaled by total assets as in Lyandres et al. (2008) and capital expenditures scaled by PPE as in Polk and Sapienza (2009). In untabulated results we continue to find that these variables of investment do not perform as strongly as growth in total assets.

It could be that the momentum and reversal effect we document is driven by an alternative variable that is correlated with investment but is not investment. It may be that the true relationship is an alternative specification of Eq. (2) that substitutes some other variable for investment. We consider three such variables: growth in revenue, growth in debt, and growth in equity.[11] To investigate, we re-estimate the regressions in Panel B of Table 3 while adding these additional variables as additional regressors. In these untabulated tests, we find none of these measures maintain the same relationship with the momentum and reversal effect, as does our investment variable – total asset growth. The effect we document appears to be unique to investment, as it is investment, and not some other measure that is correlated with investment, that explains the momentum and reversal effects.

3.4. Causation

While the results presented in Section 3.3 provide strong evidence of a connection between momentum effects and investment we are not able to infer causation. The problem is that both the momentum-based holding period returns and investment are measured contemporaneously. It may be that the subsequent investment generates a momentum effect as proposed in this paper, or alternatively that the subsequent strong momentum effects generate contemporaneous investment.

While we are not able to fully resolve this concern in this paper, we do try to present some additional tests of the unique nature of the investment–momentum relationship. In the first test we show that while contemporaneous investment drives away the independent predictability of past returns, it does not drive away the predictability of a set of other predictive variables. To do this, we run regressions identical to those in Table 3, Panel B except that we substitute various other predictive firm variables in place of past returns. The variables we select are Operating Accruals (Sloan, 1996; Hribar and Collins, 2002), Net Operating Assets (Hirshleifer et al., 2004), and Book-to-Market ratio (Davis et al., 2000). Operating Accruals is the change in noncash working capital minus depreciation (DPQ). The change in noncash working capital is computed as the change in current assets (ACTQ), minus change in cash and cash equivalents (CHEQ) minus change in current liabilities (LCTQ) plus change in debt included in current liabilities (DLCQ) plus change in income taxes payable (TXPQ). Missing changes in income taxes payable are set to zero. Starting in 1988 we measure operating accruals using the statement of cash flows as net income (NIQ) minus net cash flow from operations (OANCFY). We scale operating accruals by lagged total assets. Net operating assets is operating assets minus operating liabilities scaled by lagged total assets, where operating assets are total assets (ATQ) minus cash and cash equivalents (CHEQ). Operating liabilities are total assets minus debt included in current liabilities (DLCQ, zero if missing), minus long-term debt (DLTTQ, zero if missing), minus minority interest (MIBQ, zero if missing), minus preferred stock (PSTKQ, zero if missing) minus common equity (CEQQ). In the tests we use the six-month average for the Net Operating Assets and Operating Accruals variables to match our approach with our investment measure. While the literature for these predictive variables does not necessarily suggest that a lag structure is necessary, we maintain the lag structure to be consistent with the tests in Table 3.

[11] Growth in revenue is the sum of the quarterly percentage growth in sales for two consecutive quarters (Compustat Data Item 'SALEQ). Growth in equity and growth in debt are measured as the quarterly change in the variable divided by initial total assets, and are the sum of their growth for two consecutive quarters. Equity is common equity (CEQQ) plus preferred stock (PSTKQ) plus minority interest (MIBQ) minus retained earnings (REQ). Debt is the sum of long and short term debt (DLTTQ and DLCQ).

Table 4
Regression estimates to test impact of alternative variables and samples on returns.

Panel A. The predictive power of alternative variables on returns and their interaction with investment

	Definition of variable (VarX)								
	Operating accruals			Net operating assets			Book-to-market ratio		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
D(VarX(−1) = High)	−0.002*	−0.000	−0.000	−0.003*	−0.003***	−0.002***	0.006***	0.008***	0.009***
	(1.86)	(−0.10)	(−0.54)	(−5.73)	(−4.44)	(−3.74)	(4.10)	(6.04)	(6.83)
D(VarX(−1) = Low)	0.004***	0.004***	0.004***	0.005***	0.005***	0.006***	−0.002	0.005***	0.005***
	(6.15)	(5.89)	(6.48)	(4.66)	(4.97)	(5.31)	(1.15)	(3.21)	(2.78)
D(VarX(−2) = High)	−0.004***	−0.004***	−0.005***	−0.002***	−0.005***	−0.004**	−0.002	−0.002*	−0.003**
	(−4.62)	(−6.15)	(−6.71)	(−3.40)	(−6.21)	(−5.99)	(−1.57)	(−1.80)	(−2.16)
D(VarX(−2) = Low)	0.001*	0.001	0.001*	−0.002*	−0.001	−0.000	−0.002	−0.002	−0.001
	(1.66)	(1.53)	(1.67)	(−2.27)	(−1.07)	(−0.41)	(−1.61)	(−1.23)	(−0.40)
D(Inv(+ 1) = High)		0.020***	0.018***		0.019***	0.20***		0.020***	0.020***
		(13.61)	(12.42)		(13.81)	12.51)		(13.64)	(13.81)
D(Inv(+ 1) = Low)		−0.019***	−0.018***		−0.020***	−0.019**		−0.020***	−0.018***
		(−13.38)	(−13.13)		(−13.52)	(−12.12)		(−13.45)	(−12.54)
D(VarX(−1) = High) × D(Inv(+ 1) = High)			0.001			−0.002			−0.011***
			(0.89)			(−1.08)			(−5.57)
D(VarX(−1) = Low) × D(Inv(+ 1) = Low)			−0.001			−0.001			−0.004
			(−1.25)			(−0.55)			(−1.53)
D(VarX(−2) = High) × D(Inv(+ 1) = High)			0.004***			−0.001			0.005**
			(2.83)			(−0.64)			(2.56)
D(VarX(−2) = Low) × D(Inv(+ 1) = Low)			−0.000			−0.002			−0.005***
			(−0.13)			(−1.21)			(−2.63)
Past Month Return	−0.038***	−0.053***	−0.053***	−0.038***	−0.053***	−0.053***	−0.036***	−0.051***	−0.051***
	(−5.90)	(−8.37)	(−8.43)	(−6.16)	(−8.90)	(−8.95)	(−6.03)	(−8.69)	(−8.73)
Book-to-market ratio	0.002*	0.005***	0.005	0.003***	0.006***	0.006***	0.000	0.001	0.001
	(1.84)	(4.53)	(4.54)	(2.52)	(5.58)	(5.61)	(0.01)	(1.07)	(0.91)
Market cap	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(−1.01)	(−1.06)	(−1.07)	(−0.47)	(−0.66)	(−0.67)	(−0.07)	(−0.15)	(−0.24)
Intercept	0.016***	0.016***	0.016*	0.015***	0.016***	0.016**	0.012**	0.011**	0.011**
	(3.26)	(3.49)	(3.52)	(2.98)	(3.39)	(3.36)	(2.30)	(2.34)	(2.30)
Mean R-squared	0.039	0.053	0.056	0.036	0.051	0.053	0.037	0.051	0.054

Panel B. The impact of investment on momentum in alternative sub-samples

	Whole sample		High turnover		Non-investment grade		No analyst following	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D(Ret(−1) = High)	0.006***	0.002	0.005***	−0.000	0.007***	0.003**	0.010***	0.006**
	(4.89)	(1.39)	(3.26)	(−0.08)	(5.45)	(1.99)	(4.84)	(2.36)
D(Ret(−1) = Low)	−0.006***	−0.001	−0.006***	−0.000	−0.006***	−0.001	−0.009***	−0.003*
	(−3.36)	(−0.48)	(−3.13)	(−0.05)	(−3.54)	(−0.68)	(−5.13)	(−1.72)
D(Ret(−2) = High)	0.004***	0.000	0.004***	−0.000	0.004***	0.001	0.006***	0.002
	(3.02)	(0.18)	(3.06)	(−0.03)	(3.32)	(0.52)	(2.82)	(1.1)
D(Ret(−2) = Low)	−0.005***	−0.002	−0.004**	0.001	−0.005***	−0.002	−0.005***	−0.004**
	(−3.24)	(−1.18)	(−2.05)	(0.45)	(−3.37)	(−1.31)	(−2.94)	(−2.36)
D(Inv(+ 1) = High)		0.016***		0.019***		0.017***		0.015***
		(13.76)		(10.53)		(13.41)		(8.70)
D(Inv(+ 1) = Low)		−0.016***		−0.021***		−0.017***		−0.013***
		(−13.96)		(−11.63)		(−14.11)		(−9.17)
D(Ret(−1) = High) × D(Inv(+ 1) = High)		0.009***		0.008***		0.008***		0.011***
		(5.83)		(4.36)		(5.26)		(2.96)
D(Ret(−1) = Low) × D(Inv(+ 1) = Low)		−0.007***		−0.006**		−0.006***		−0.009***

(continued on next page)

Table 4 (*continued*)

Panel B. The impact of investment on momentum in alternative sub-samples

	Whole sample		High turnover		Non-investment grade		No analyst following	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		(−4.57)		(−2.59)		(−3.86)		(−3.2)
D(Ret(−2) = High) × D(Inv(+ 1) = High)		0.007***		0.007***		0.006***		0.007**
		(4.94)		(3.09)		(4.38)		(2.21)
D(Ret(−2) = Low) × D(Inv(+ 1) = Low)		−0.005***		−0.008***		−0.004***		−0.004
		(−3.94)		(−3.14)		(−3.32)		(−1.51)
Past Month Return	−0.039***	−0.052***	−0.023***	−0.041***	−0.039***	−0.054***	−0.048***	−0.060***
	(−6.72)	(−9.21)	(−3.65)	(−6.38)	(−6.79)	(−9.34)	(−7.89)	(−9.50)
Book-to-market ratio	0.005***	0.007***	0.006***	0.010***	0.005***	0.008***	0.006***	0.008***
	(4.30)	(7.30)	(4.81)	(8.78)	(4.54)	(7.64)	(5.98)	(8.40)
Market cap	−0.000	−0.000	0.000	0.000	−0.000	−0.000	−0.001*	−0.001*
	(−0.38)	(−0.22)	(0.63)	(0.69)	(−0.52)	(−0.93)	(−1.75)	(−1.96)
Intercept	0.013***	0.013***	0.009	0.010	0.014***	0.015***	0.017***	0.017***
	(2.98)	(3.04)	(1.35)	(1.45)	(3.22)	(3.61)	(4.43)	(4.55)
Mean R-squared	0.047	0.064	0.054	0.081	0.045	0.062	0.059	0.087

This table reports regression estimates for gross stock returns. The Fama–MacBeth regressions are estimated monthly, and we report the average of these coefficients. The dependent variable is monthly returns. Regarding the independent variables, the holding period for both returns and growth rates is on a half-year basis. The gross stock return is the monthly total return for the firm from CRSP. The investment rate (Inv) is defined as the six-month growth in total assets from the quarterly Compustat file. Market cap is defined as the market value of equity as of the month before we measure the dependent variable divided by 1000. Operating accruals is changes in noncash working capital minus depreciation (DPQ). Changes in noncash working capital is computed as the change in current assets (ACTQ), minus change in cash and cash equivalents (CHEQ) minus change in current liabilities (LCTQ) plus change in debt included in current liabilities (DLCQ) plus change in income taxes payable (TXPQ). Missing changes in income taxes payable are set to zero. Starting in 1988 we measure operating accruals using the statement of cash flows as net income (NIQ) minus net cash flow from operations (OANCFY). We scale operating accruals by lagged total assets. Net operating assets are operating assets minus operating liabilities scaled by lagged total assets, where operating assets are total assets (ATQ) minus cash and cash equivalents (CHEQ). Operating liabilities are total assets minus debt included in current liabilities (DLCQ, zero if missing), minus long-term debt (DLTTQ, zero if missing), minus minority interest (MIBQ, zero if missing), minus preferred stock (PSTKQ, zero if missing) minus common equity (CEQQ). The book-to-market ratio is as of the fiscal quarter before we measure the dependent variable. To control for outlier effects in the regression, all continuous variables except returns are log transformed, and all independent variables are winsorized at the 0.5% and 99.5% levels. The Past Month Return is defined as the monthly return for the month prior to the month before we measure the dependent variable. The variable timings vary, and we include in parentheses the timings in relation to the dependent variable in half-years, such that −1 is the half-year before the dependent variable and + 1 is the half-year contemporaneous to the dependent variable. A slight adjustment is made for Ret(−1) to exclude Past Month Return so that Ret(−1) is defined as cumulative gross return for months −6 to −2. We include various dummy variables indicating the top and bottom quintiles of the variable in question. The High Turnover Only sample contains firms in the top turnover tercile, where turnover is defined as the past 6-month average of monthly volume scaled by shares outstanding. The Non-Investment Grade Only sample is defined as firms with an S&P firm rating below BBB-, or that have no credit rating. The No Analyst Coverage Only sample is defined as those firms that do not have analyst coverage on IBES during the month prior to the holding period. The standard errors are adjusted for serial correlation, and *** denote significance at the 1% level, ** at the 5% level and * at the 10% level.

We report our results in Panel A of Table 4. In regression specifications 1, 4, and 7 we report the base case estimates where investment is not included. We observe various significant relations between each variable and subsequent returns, with a negative relation for operating accruals and net operating assets, and a positive relation for book-to-market ratio. In regression specifications 2, 5, and 8 we report the estimates of coefficients on these variables with the addition of subsequent firm investment levels, and in regression specifications 3, 6, and 9 we report the estimates of coefficients on these variables with the addition of interaction variables with subsequent firm investment levels. The test results indicate that the impact of subsequent firm investment is much less pronounced on the predictive effect of these variables than for past returns. For the most part, the addition of firm investment in isolation and as an interaction term has little effect on the overall predictive power of operating accruals, net operating assets, and book-to-market ratio, where it maintains strong impact on the predictive power of past returns. The result provides an indication of the unique nature of the relation between momentum and investment effects.

In an additional test, we again repeat the test of Panel B of Table 3, but instead substitute the three predictive variables for investment. As such we identify whether subsequent realizations in operating accruals, for example, has an effect on dampening the predictive power of past returns. While we do not report these tests in the tables, we find that the subsequent realization of the other predictive variables shows no effect on the predictive power of past returns. The momentum effect is strong regardless of the firm's subsequent accrual, net operating asset, or book-to-market ratio level. These results again emphasize the unique relation between investment and momentum. While these tests establish the unique nature of the investment–momentum relationship, they do not allow us to establish causation.

3.5. Cross-sectional effects

In this section we investigate whether the results documented in the previous section are robust to previous momentum effects documented in the literature. In particular, we investigate how our results change, when we stack the odds against them, by looking specifically in the sub-samples that are known to display particularly large momentum effects. Studies that observe interrelations with momentum include findings for share turnover (Lee and Swaminathan, 2000), analyst coverage (Hong et al., 2000), credit rating (Avramov et al., 2013), valuation ratios (Asness, 1997; Daniel and Titman, 2006), trading costs (Lesmond et al., 2004), information uncertainty (Zhang, 2006), and dispersion in analyst earnings forecasts (Verardo, 2009). We specifically consider Lee and Swaminathan (2000) who document that momentum effects are correlated with the level of share turnover; Avramov et al. (2013) that document that momentum is isolated among firms with non-investment grade credit ratings; and Hong et al. (2000) who observe that analyst coverage provides an important cross-sectional effect in momentum.

To test whether our investment analysis is independent of these cross-sectional momentum effects, we run our regression tests on sub-samples of firms that demonstrate the particular characteristic from the literature. We report these results in Panel B of Table 4. In these tests, we again use the same regression specifications as in Panel B of Table 3.

In the first regressions we provide a baseline full sample test. This is a replication of the first two regressions in Panel B of Table 3. In specifications 3 and 4 we follow Lee and Swaminathan and restrict the sample to only include those firms that maintain turnover ratios among the top tercile for the previous half-year. Turnover is defined as the 6 month average of monthly volume scaled by shares outstanding. Both variables are obtained from CRSP. Specification 3 provides the regression estimates for the sample of only high turnover stocks. Yet, the explanatory power of past performance in isolation found in the base case (Regression 3) is eliminated once the interaction terms with firm investment are included. For example, the coefficient on D(Ret(−1) = High) drops to −0.00 (t-stat = −0.08) and the coefficient on D(Ret(−1) = Low) drops to −0.00 (t-stat = −0.05) in Specification 4. The results support the conclusion that there is no residual momentum effect among the high turnover stocks.

In specifications 5 and 6 we restrict the sample to only include those firms that maintain non-investment grade or missing credit ratings for the previous half-year. Credit rating is from Compustat and is the S&P issuer rating. Following Avramov, et al., a firm is non-investment grade if its credit rating is below BB+. In this test the explanatory power of past performance in isolation found in the base case (Regression 5) is greatly diminished once the interaction terms with investment are included. The coefficient on D(Ret(−1) = High) drops from 0.007 (t-stat = 5.45) to 0.003 (t-stat = 1.99) and the coefficient on D(Ret(−1) = Low) drops from −0.006 (t-stat = −3.45) to −0.001 (t-stat = −0.68). The coefficients on the twice lagged returns are no longer significant once firm investment is included. We conclude that firm investment policy largely explains the momentum effect among non-investment grade firms.

In Regressions 7 and 8, we conduct a final cross-sectional test for the subsample that includes only those firms for which there is no analyst coverage on IBES during the month prior to the holding period. In Regression 7 following Hong et al. (2000), we observe that firms with no analyst coverage appear to maintain a particularly large momentum effect. When we include the interaction variables with investment, again the explanatory power of past returns in isolation are substantially reduced although not eliminated. For Regression 8, the coefficient on D(Ret(−1) = High) drops from 0.010 (t-stat = 4.84) to 0.006 (t-stat = 2.36) and the coefficient on D(Ret(−1) = Low) drops from −0.009 (t-stat = −5.13) to −0.003 (t-stat = −1.72). We conclude that firm investment policy largely explains the momentum effect among firms without analyst following. The tests in Table 4 indicate that our investment-based explanation of momentum is not simply a manifestation of some of the existing cross-sectional effects already in the literature and largely explains momentum effects in these subsamples where such effects have been found to be largest.

3.6. Reversal and investment

We conduct a similar exercise for the reversal effect. In order to capture the longer horizons associated with return reversals, the dependent variable in these tests is the half-year gross return and the regression is estimated each half-year as in Table 2, rather than monthly. D(Ret(−3) = High) is defined as indicating that returns in half year −3 are among the top 20 percent. A similar definition follows for the other indicator variables.

Regression results are reported in Table 5. In regression specification 1 we provide baseline results. We observe that the mean coefficient estimate for D(Ret(−3) = High) is -0.016 (t-stat = −3.02) and the coefficient on D(Ret(−3) = Low) is positive at +0.005 but not significant (t-stat = 0.99). The test confirms a reversal effect in that past winners tend to do poorly over long horizons. In specification 2 we add an additional set of dummy variables that indicate whether the subsequent investment in the following half year period (−2) was among the top 20th D(Inv(−2) = High) or bottom 20th levels D(Inv(−2) = low). We also estimate coefficients for interaction values in which past winners subsequently expand and past losers subsequently contract. In this specification we observe that the coefficients on the interaction terms are not significant but their inclusion creates a dampening effect on the reversal result. The coefficient on D(Ret(−3) = High) is now −0.011 (t-stat = −2.29) and the coefficient on D(Ret(−1) = Low) is now 0.004 (t-stat 0.94). The evidence suggests that the reversal effect is not fully eliminated by the inclusion of the single specification of subsequent investment at time 2.

The establishment of the investment period as −2 is ad hoc. We suspect that the test of investment-based reversals would be more discriminating if the investment horizon was more general. In Specification 3 we add an additional set of dummy variables that indicate whether the investment in half-year −3 was among the top 20th D(Inv(−3) = High) or bottom 20th levels D(Inv(−3) = Low). We also estimate coefficients for interaction values in which past winners expand and past losers contract. We include these additional timing effects because of the ad hoc nature in which we specify timing in our tests. It is certainly possible that the return horizons associated with investment may also occur at either 18 months or 24 months previously. When we add Inv (−3), we observe that the coefficients on the interaction terms are still significant for the winners as in the baseline regression. In our final specification we include both sets of investment variables, Inv(−2) and Inv(−3). We note that their dual inclusion maintains an important effect on the base reversal

Table 5
Regression estimates to examine reversal effects.

	(1)	(2)	(3)	(4)
D(Ret(−3) = High)	−0.016***	−0.011**	−0.009*	−0.006
	(−3.02)	(−2.29)	(−1.96)	(−1.41)
D(Ret(−3) = Low)	0.005	0.004	0.005	0.004
	(0.99)	(0.94)	(1.00)	(0.89)
D(Inv(−2) = High)		−0.024***		−0.022***
		(−4.49)		(−4.13)
D(Inv(−2) = Low)		−0.004		−0.002
		(−1.17)		(−0.69)
D(Ret(−3) = High) × D(Inv(−2) = High)		−0.006		−0.003
		(−1.34)		(−0.56)
D(Ret(−3) = Low) × D(Inv(−2) = Low)		0.004		0.004
		(0.78)		(0.64)
D(Inv(−3) = High)			−0.018***	−0.016***
			(−3.56)	(−3.38)
D(Inv(−3) = Low)			−0.002	−0.001
			(−0.57)	(−0.23)
D(Ret(−3) = High) × D(Inv(−3) = High)			−0.016***	−0.014**
			(−2.90)	(−2.47)
D(Ret(−3) = Low) × D(Inv(−3) = Low)			0.001	0.000
			(0.12)	(0.00)
Book-to-market ratio(−1)	0.013*	0.010	0.011*	0.009
	(1.92)	(1.59)	(1.76)	(1.50)
Market cap(−1)	−0.000	−0.001	−0.001	−0.001
	(−0.11)	(−0.27)	(−0.27)	(−0.35)
Intercept	0.076***	0.082***	0.081***	0.084***
	(3.32)	(3.61)	(3.54)	(3.75)
Mean R-squared	0.042	0.047	0.048	0.052

This table reports regressions estimates for stock returns. The holding period for both returns and investment is on a half-year basis where the half-year is measured from January to June and from July to December. The gross stock return is the cumulative monthly total return for the firm from CRSP. Fama–MacBeth cross-sectional regressions are estimated every half year and the mean coefficient estimates are reported. The investment rate (Inv) is defined as the six-month growth in total assets from the quarterly Compustat file. Market cap is defined as the market value of equity as of the quarter before we measure the dependent variable divided by 1000. The book-to-market ratio is as of the fiscal quarter before we measure the dependent variable. To control for outlier effects in the regression, all continuous variables except returns are log transformed and all variables are winsorized at the 0.5% and 99.5% levels. We include various dummy variables indicating the top and bottom quintiles of asset growth and returns. The variable timings vary, and we include in parentheses the timings in relation to the dependent variable in half-years, such that −1 is the half-year before the dependent variable and +1 is the half-year contemporaneous to the dependent variable. The standard errors are adjusted for serial correlation, and *** denote significance at the 1% level, ** at the 5% level and * at the 10% level.

variables. The coefficient on D(Ret(−3) = High) drops to −0.006 (t-stat = −1.41) and the coefficient on D(Ret(−3) = Low) is now 0.004 (t-stat 0.89). We see that controlling for the firm's investment policy over the two half-years fully drives out the independent reversal effect of past returns over long horizons.

It could be that the reversal effect we document is driven by an alternative variable that is correlated with investment but is not investment. For example, Lakonishok et al. (1994) observe a strong negative correlation between sales growth and subsequent returns. It may be that the true relationship is an alternative specification of Eq. (3) that substitutes sales growth for investment, consistent with the Lakonishok, Shleifer, and Visnhy findings. To investigate the relationship between their finding and ours, we re-estimate the regressions in Table 5 as well as Panel B of Table 3 while substituting revenue growth variables for investment variables, similar to what we did in Section 3.3. In these untabulated tests, we find that despite the strong correlation that revenue growth maintains with returns, revenue growth does not maintain the same relationship with the momentum and reversal effect, as does our investment variable asset growth: revenue growth is insufficient and asset growth is required in the specification to eliminate the explanatory power of past returns. We repeat this same analysis with two other variables (growth in debt and growth in equity). Again we find that these other measures are insufficient and our measure of investment is required to eliminate the explanatory power of past returns.

Overall, these tests provide evidence that both the momentum and reversal effects are jointly explained through the firm's investment policy. The findings are consistent with return shocks that are associated with subsequent investment shocks, and investment that is positively correlated with contemporaneous returns and negatively correlated with subsequent returns. In our regression framework, we find empirical support for the prediction that the momentum and reversal effects in returns exist only in association with the prescribed firm investment policy.

Table 6
Portfolio returns based on past returns.

	Low returns	2	3	4	High returns	High–Low
Panel A. Sorted by gross returns for half-year −1						
Mean monthly gross returns for half-year +1	0.0063	0.0103	0.0117	0.0123	0.0152	0.0089*** (3.49)
Mean monthly FF-abnormal returns for half-year +1	−0.0070*** (−3.39)	−0.0018* (−1.86)	0.0000 (−0.01)	0.0007 (1.42)	0.0032*** (3.96)	0.0103*** (3.98)
Mean investment rates for half-year +1	0.0112	0.0301	0.0362	0.0449	0.0718	0.0606*** (44.05)
Panel B. Sorted by gross returns for half-year −2						
Mean monthly gross returns for half-year +1	0.0091	0.0115	0.0121	0.0128	0.0123	0.0032** (2.08)
Mean monthly FF-abnormal returns for half-year +1	−0.0043*** (−3.42)	−0.0008 (1.15)	0.0004 (0.74)	0.0013** (2.01)	0.0001 (0.15)	0.0044*** (3.03)
Mean investment rates for half-year +1	0.0192	0.0302	0.0354	0.0427	0.0620	0.0428*** (46.43)
Panel C. Sorted by gross returns for half year −2						
Mean monthly gross returns for half-year +1	0.0134	0.0126	0.0123	0.0115	0.0090	−0.0043*** (−3.45)
Mean monthly FF-abnormal returns for half-year +1	−0.0001 (−0.10)	0.0004 (0.57)	0.0006 (1.07)	−0.0001 (−0.12)	−0.0030*** (−3.16)	−0.0029** (−2.51)

This table reports monthly portfolio returns and respective investment rates. The portfolios are formed based on 6-month lagged returns and held for 6 months and equal weighted across stocks. The timing is expressed in 6 month periods, and half-year −1 refers to half year before the holding period, and half-year +1 is the holding period. In panel A portfolios are sorted on the 6-month returns prior the holding period; in panel B portfolios are sorted on the 6-month returns 6 months ago; and in panel C portfolios are sorted on the 6-month returns 12 months ago. The stocks are grouped in quintiles, and the last column contains portfolios returns for a portfolio that is long on the highest return quintile and short on lowest return quintile. We present mean gross portfolios returns, the intercepts of a 3-factor Fama–French (FF) model and the 6-month asset growth rate for the firms in the portfolio. T-statistics are in parentheses, and *** denote significance at the 1% level, ** at the 5% level and * at the 10% level.

4. Portfolio returns

4.1. *Return effects*

We now turn to traditional portfolio tests to more closely examine the economic magnitudes of the interrelation between returns and investment. To replicate the underlying return effects, we form momentum portfolios in a manner similar to Jegadeesh and Titman (1993). Each month securities are sorted into quintiles on the basis of their returns in the past 6 months. The position is then held for 6 months, and each month, the strategy closes out the position initiated 6 months ago. Hence, under this trading strategy we revise the weights on 1/6th of the securities in the entire portfolio in any given month and carry over the rest from the previous months.

In Panel A of Table 6 we report the mean monthly gross returns and Fama–French three-factor alphas by past return quintile. We observe the common momentum effect with a monotonic increase in mean returns based on past half-year performance. The difference in monthly gross returns for the winners (1.52%) and the losers (0.63%) is 0.89% (t-stat = 3.49). The difference in three-factor alphas for the winners (0.32%) and the losers (−0.70%) is 1.03% (t-stat = 3.98). Our sample appears to generate the common momentum effect in stock returns over a six-month horizon. We observe a strong correlation between past returns and subsequent investment. Firms in the low return quintile maintain a mean half-year asset growth rate of 1.1%, whereas firms in the high return quintile maintain a mean half-year asset growth rate of 7.2%. The difference in investment rates is highly statistically significant, consistent with the previous observation that past winners tend to invest substantially more than past losers.

In Panel B we repeat the same exercise but with sorts based on returns for half-year −2. We observe that high minus low return spreads are again positive and significant with a spread of 0.32% (t-stat = 2.08) for gross returns and 0.44% (t-stat = 3.03) for adjusted returns. Although significant the spread is smaller than that observed at a six-month horizon. Nevertheless, we continue to observe strong associations with investment. The evidence suggests that in this set up the investment may be most responsive in horizons under 6–12 months.

Finally, in Panel C we report the subsequent mean returns for firms sorted based on their returns in half-year −3. In this panel, the relevant investment rates are for Years −1 and −2, since the prediction is that the return reversal occurs after the investment. The mean investment rates for these periods are reported in Panels A and B. One can note a negative correlation between the investment rates in Panels A and B and the subsequent returns in Panel C. This lag structure represents a delay of more than 12 months. Based on this sorting we observe a significant reversal in subsequent returns. The mean monthly gross returns for stocks in the low-return quintile are 1.34% and the returns for stocks in the high-return quintile are 0.90% for a statistically significant difference of −0.43% (t-stat = −3.45). The mean monthly three-factor alpha for stocks in the low-return quintile are −0.01% and the returns for stocks in the high-return quintile are −0.30% for a statistically significant difference of −0.29% (t-stat = −2.51). This evidence is consistent with return reversal as in DeBondt and Thaler (1985, 1987). The findings in this table are consistent with a term structure of stock returns that is positively correlated over moderate horizons and negative over long horizons.

Table 7
Portfolio returns with investment interaction.

Panel A. Abnormal returns for momentum portfolios

		Sorted by gross returns for half-year −1					High–Low
		Low returns	2	3	4	High returns	
Sorted by investment for half-year +1	Low Inv	−0.0205*** (−8.01)	−0.0145*** (−11.88)	−0.0120*** (−14.40)	−0.0112*** (−15.52)	−0.0126*** (−13.02)	0.0079*** (2.91)
	2	−0.0056*** (−2.87)	−0.0042*** (−4.13)	−0.0032*** (−4.79)	−0.0035*** (−5.77)	−0.0058*** (−7.54)	−0.0002 (−0.11)
	3	−0.0014 (−0.79)	0.0000 (0.03)	0.0007 (1.06)	−0.0003 (−0.50)	−0.0018** (−2.13)	−0.0004 (−0.18)
	4	0.0014 (0.75)	0.0031*** (3.32)	0.0038*** (5.39)	0.0039*** (6.07)	0.0054*** (5.65)	0.0040* (1.67)
	High Inv	0.0039** (2.22)	0.0060*** (6.20)	0.0067*** (9.29)	0.0082*** (11.43)	0.0130*** (11.29)	0.0091*** (3.81)

Panel B. Abnormal returns for reversal portfolios

		Sorted by gross returns for half-year −2					High–Low
		Low returns	2	3	4	High returns	
Sorted by investment for half-year −2	Low Inv	0.0005 (0.38)	0.0010 (1.40)	0.0014** (2.26)	0.0007 (1.00)	−0.0020* (−1.80)	−0.0025* (−1.91)
	2	0.0012 (1.17)	0.0013** (2.05)	0.0016*** (2.75)	0.0017*** (2.58)	−0.0007 (−0.70)	−0.0019 (−1.52)
	3	0.0009 (0.88)	0.0015** (2.25)	0.0015*** (2.59)	0.0009 (1.37)	−0.0006 (−0.59)	−0.0015 (−1.20)
	4	0.0001 (0.07)	0.0001 (0.14)	0.0004 (0.61)	0.0000 (0.06)	−0.0012 (−1.15)	−0.0012 (−0.97)
	High Inv	−0.0047*** (−3.18)	−0.0039*** (−4.16)	−0.0037*** (−4.21)	−0.0042*** (−4.36)	−0.0071*** (−6.04)	−0.0025** (−1.98)

This table reports monthly portfolio returns for momentum (Panel A) and reversal (Panel B) effects. The returns are equal weighted across stocks and adjusted based on the Fama–French three-factor model. The timing is expressed in 6-month periods, such that half-year −1 refers to half-year before the holding period, and half-year +1 is the holding period. Portfolios are independently sorted on two-way quintiles: the 6-month asset growth investment contemporaneous to the holding period (half-year +1) and the 6-month returns prior to the holding period (half-year −1) (Panel A) and the 6-month returns 1-year before the holding period (half-year −2), and the subsequent asset growth (half-year −2) (Panel B). The last column contains portfolios returns for a portfolio that is long on the highest return quintile and short on lowest return quintile. T-statistics are in parentheses, and *** denote significance at the 1% level, ** at the 5% level and * at the 10% level.

4.2. Investment effects

We now use two-way independent sorts to identify the relation of the momentum and reversal effects with respect to investment policy. To examine momentum effects, we sort firms independently into quintiles by returns in half-year −1 and by investment rate in half-year +1. This sorting is motivated by the evidence observed that the momentum effect is isolated among those firms with extreme high or low investment rates. Our test is to observe whether momentum spreads are uniform across subsequent investment rates or whether they disappear for firms without abnormal investment as in Table 3. In these independently formed portfolios the mean number of stocks in the portfolios range from 70 in the low investment-high past returns portfolio to 173 in the low investment-low past returns portfolio.

We report the mean monthly-adjusted returns in Panel A of Table 7. The first pattern we observe is that low investment firms systematically maintain low adjusted returns across all return quintiles and high investment firms maintain high returns across all return quintiles. Investment is contemporaneously associated with high returns. Next, we look across past return quintiles and observe that the significant momentum spreads are isolated to only those firms that experience subsequent extreme investment rates.[12] For firms with the highest investment rates, the high-minus-low half-year momentum spread is 0.91% (t-stat = 3.81). For firms with the lowest asset growth rates, the high-minus-low momentum spread is 0.79% (t-stat = 2.91). Most importantly, for the middle investment group (investment quintile 3), there is no momentum spread as the winner-less-loser spread is −0.04% (t-stat = −0.18). The variation in momentum effect is highly dependent on investment policy and driven by the firms in the extreme portfolios. Our evidence in this test is consistent with that of the regression format in Table 3 in that we observe no unconditional momentum

[12] The fundamental difference between this result and that of the Nyberg and Poyry (2014) result is that Nyberg and Poyry is based on past investment while this test is based on subsequent investment in order to identify the source of the effect.

effect—meaning that there is no momentum effect in the absence of abnormal subsequent investment. While we observe strong momentum effects in the extreme investment portfolios, the existence of momentum in these cases is not necessarily predicted by our model (we do not have an expectation of the comparison of firms that experience poor past returns and then strongly invest).

We conduct a similar test for return reversals. To examine reversal effects, we sort firms independently into quintiles by returns in half-year −3 and by asset growth rate in half-year −2. This sorting is motivated by the assertion that the reversal effect is non-existent among those firms in which a return shock does not motivate subsequent investment. Our test is to observe whether reversal spreads are uniform across subsequent investment rates or rather non-existent among those firms without subsequent abnormal investment. The mean number of stocks in the portfolios vary from 66 in the high growth-low returns portfolio to 140 in the low growth-low returns portfolio.

We report the mean monthly risk-adjusted returns in Panel B of Table 7. As we look at quintiles based on past returns we observe across the high-minus-low reversal spreads that the significant spreads are again isolated to only those firms that experience subsequent extreme asset growth rates. For firms with the highest asset growth rates, the high-minus-low reversal spread is −0.25% (t-stat = −1.91). For firms with the lowest asset growth rates, the high-minus-low reversal spread is −0.25% (t-stat = −1.98). For the meddling investment group (investment quintile 3), the reversal spread is −0.15% (t-stat = −1.20). Again, the variation in the reversal effect is driven by the firms in the extreme portfolios and is lacking among those without abnormal investment. Since our portfolio tests only allow us to control for investment at one point in time, the results in Table 5 potentially provide a more complete description of the interactions of various leads and lags. Still, the evidence is consistent with an important role for investment in the reversal pattern as reversal effects are determined jointly with the prescribed return-based investment policy and correlated with the unwinding reversal of momentum overreaction. Moreover, because both the past returns and investment values are known at the sorting date, the strategy documented in Panel B is a strategy that could be executed. The enhanced reversal strategy would buy stocks with low past returns and low investment and sell stocks with high past returns and high investment. Based on the results in Panel B, the long leg generates returns of 0.05% while the short leg generates returns of −0.71%, for a spread of 0.76% per month. This spread in returns is larger than the 0.29% spread observed in the naïve reversal strategy (Panel C of Table 6). Even wider spreads are achieved for less extreme portfolios on the long side.

Fig. 1 provides a long horizon presentation of the behavior of returns sorted by past returns and contemporaneous investment rates. In Panel A, we show the subsequent monthly portfolio returns of the firms with high past returns (winners) sorted by subsequent investment rates over the 24 months following the return sorting period. The graph shows the overall mean return for these firms in the light dotted line. We note over the first six months that the returns for the winners are broadly distributed around the overall mean return. The return continuation is found among those firms with high investment. Low investment winners do poorly over the first six months. Once subsequent investment is controlled for, there is no abnormal momentum return for the winner firms. Over months 7 through 24, the reversal pattern of low returns is exclusively among the higher investment firms. Clearly, the pronounced momentum and reversal is most acute for the high investment firms. In Panel B, we show the same time-series pattern for the low performance firms (losers). Again we see that over the first half-year the portfolio returns are evenly distributed around the mean return. The underperformance is concentrated among the firms with low investment. For the loser firms, the reversal effect of high long-horizon returns is non-existent for the high investment firms. The figure demonstrates the importance of investment rates in explaining both sides of the momentum and reversal effects.

4.3. Earnings announcement day returns

As discussed, our empirical observations are consistent with both rational and behavioral explanations. While an attempt to fully discriminate between these explanations is beyond the scope of this paper, we provide one test with the intent to provide some indication of the source of these effects. The test is motivated by Chan et al. (1996) who explore the source of momentum profits. In their work they examine various earnings surprise metrics – including the returns associated with earnings announcement days – to argue that momentum returns result from systematic market under reaction to fundamentals.

Similarly, we examine the returns associated with earnings announcements conditioning on past returns and investment levels. Our supposition is that if our results are rooted in a risk-based explanation then there should be no abnormal returns on earnings announcement days with respect to past return and investment levels. On the other hand, any evidence of systematic earnings announcement return effects with respect to past returns and investment is suggestive of a mispricing foundation consistent with the prediction of Chan, et al. Our test focuses on the reversal horizon since in our model any potential mispricing is not revealed until after the investment occurs. This test design also follows because earnings announcement days occurring concurrent with the investment (i.e., the momentum window) are likely to be contaminated with investment announcements. We identify earnings announcement days based on the respective Compustat code (data item RDQ). Using the daily CRSP file, we calculate the abnormal earnings announcement day returns as the mean return for the firm's equity over the three-days centered on the quarterly earnings announcement day less the mean daily return for all other trading days in the quarter.

In Table 8 we report coefficient estimates of regressions that are identical to those reported on Table 5 except that abnormal earnings announcement day returns are substituted for the monthly returns used as the dependent variable in Table 5. Specifically, the dependent variable is the average daily return for the 3 days surrounding the earnings announcement date minus the average daily return on all other days in the same calendar quarter. For ease of reporting, coefficient estimates in the table are multiplied by 100. While unreported, the regressions also include an intercept and controls for book-to-market ratio and market capitalization.

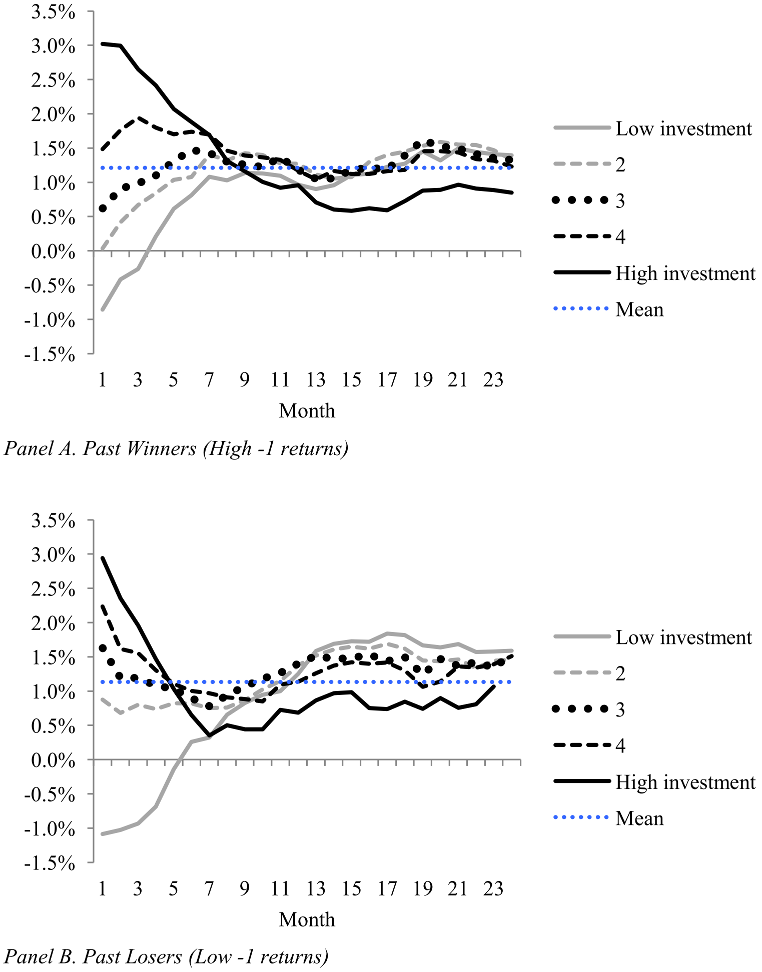

Fig. 1. Portfolio returns by month relative to sorting period. Portfolios are independently sorted on 6-month investment quintiles in period +1 and 6-month return quintiles in period −1. Panel A plots monthly portfolio returns relative to sorting period for investment portfolios in the top quintile of 6-month returns, while Panel B plots portfolio returns for the investment portfolios in the bottom quintile of 6-month returns. The mean is the overall mean of the five investment portfolios across the 24-month period.

We observe in the Regression 1 specification that returns on earnings announcement days are abnormally low for firms that had high returns two years previously. We do not find abnormally high returns for firms with prior low returns. This finding follows a similar pattern to what we observe with this data set for stock returns (i.e., a strong return reversal effect for the winners but not for the losers), and is consistent with a mispricing-based explanation for reversals. In regression specifications 2 through 4 we examine this base case result to see if the abnormal earnings announcement days returns are concentrated among those stocks that experienced subsequent investment. To do this, we follow the specifications in Table 5 with including two lag lengths and interaction terms. The coefficient on the indicator variable that flags past strong investment is negative and significant. This result is consistent with the asset growth effect (Cooper et al., 2008). We observe that when past investment is included in the regression that the significance of the coefficient on past returns declines. In regression specification 4, for example, we find no evidence of statistically significant abnormal returns associated with past returns. The clustering of abnormal returns around earnings announcement days for return reversals appears to be associated with subsequent investment, suggestive of a mispricing-based explanation.

We conduct an additional test with reversal portfolios. In this test we replicate the portfolio return tests in Panel B of Table 7, but replace abnormal earnings announcement returns instead of monthly portfolio returns. We observe a similar pattern to that of Table 7, Panel B, in that any statistically significant differences in abnormal earnings announcement returns across winner and loser portfolios are isolated to among the high investment and low investment quintiles. The fact that the variation in earnings announcement returns mirrors that of the tests using total stock returns is consistent with a behavioral bias in the market's capitalization of firm investment, and unexpected of a risk-based explanation.

Table 8
Earnings announcement returns with investment interaction.

	(1)	(2)	(3)	(4)
D(Ret(−3) = High)	−0.046***	−0.027	−0.036**	−0.020
	(−3.22)	(−1.48)	(−2.16)	(−1.02)
D(Ret(−3) = Low)	−0.016	−0.014	−0.004	−0.003
	(−1.02)	(−0.79)	(−0.20)	(−0.18)
D(Inv(−2) = High)		−0.050**		−0.047**
		(−2.08)		(−2.05)
D(Inv(−2) = Low)		−0.028		−0.025
		(−1.68)		(−1.62)
D(Ret(−3) = High) × D(Inv(−2) = High)		−0.041		−0.039
		(−1.41)		(−1.30)
D(Ret(−3) = Low) × D(Inv(−2) = Low)		0.005		0.014
		(0.18)		(0.48)
D(Inv(−3) = High)			−0.082***	−0.077***
			(−4.37)	(−4.36)
D(Inv(−3) = Low)			0.004	0.011
			(0.24)	(0.74)
D(Ret(−3) = High) × D(Inv(−3) = High)			−0.015	−0.009
			(−0.44)	(−0.26)
D(Ret(−3) = Low) × D(Inv(−3) = Low)			−0.040	−0.046
			(−1.32)	(−1.46)
Mean R-squared	0.004	0.006	0.006	0.009

This table reports regressions estimates for abnormal earnings announcement day returns. Fama–MacBeth cross-sectional regressions are estimated every half year and the mean coefficient estimates are reported. The dependent variable is the average daily return for the 3 days surrounding the earnings announcement date minus the average daily return on all other days in the same calendar quarter. To facilitate coefficient reporting, the daily returns are increased by a factor of 100. The gross stock return is the 6-month cumulative return for the firm from CRSP. The investment rate (Inv) is defined as the six-month growth in total assets from the quarterly Compustat file. The cutoffs for "high" and "low" are defined as the top and bottom quintiles for the variable period. To control for outlier effects in the regression, all continuous variables except returns are log transformed and all variables are winsorized at the 0.5% and 99.5% levels. The variable timings vary, and we include in parentheses the timings in relation to the dependent variable in half-years, such that −1 is the half-year before the dependent variable and +1 is the half-year contemporaneous to the dependent variable. While unreported, the regressions also include an intercept and controls for book-to-market ratio and market capitalization. Market capitalization is defined as the market value of equity as of the quarter before we measure the dependent variable divided by 1000. The book-to-market ratio is as of the fiscal quarter before we measure the dependent variable. T-statistics are in parentheses, and *** denote significance at the 1% level, ** at the 5% level and * at the 10% level.

4.4. Trading opportunities

Given the important interaction between investment and past return effects, one wonders about the ex-ante predictability of returns and the associated trading opportunities. Since the sorting variables used to examine the reversal effect are known prior to the holding period, these returns represent "tradable strategies" as suggested in the last section.

Since the investment rates used to examine the momentum strategies are realized contemporaneously with the holding period, the interaction effect documented in the momentum tests of this paper is not tradable. To examine what abnormal returns might be observable ex-ante, we use the predicted value from a regression similar to Regression 4 of Table 2.[13] The coefficients of Regression 3 show how important past returns are in predicting firm investment. This predictability may generate a predicted value that is useful in explaining subsequent firm returns. We should note that the sorting variable (predicted investment) is based on an in-sample estimate. The predictability of investment is likely to be less strong with an out-of-sample prediction. In Panel A of Table 9 we report mean returns for portfolios formed using this predicted investment in a two-way sort with past returns. Since we only use a predicted value of investment in the sort, all values in the sorting are available at the end of period −1.

The anticipated enhanced momentum strategy is to buy the stocks with high returns and high predicted investment while selling the stocks with low returns and low predicted investment. This strategy generates monthly abnormal returns of 0.60% (t-stat = 5.31) on the long side and −0.71% (t-stat = −2.85) on the short side, for a long-short spread of 1.31%. This spread improves on the unconditional momentum spread of 1.03% reported in Panel A of Table 6. In unreported tests, we repeat the exercise for

[13] For this test, we run the specification in Table 2, Regression 4 except that we drop the variable Inv(−1) and lag by 1 quarter all other financial statement regressors: Capital intensity, ROA, LogAssets and Book-to-market. Financial statements become available to market participants with a delay and by lagging these regressors we ensure that this trading strategy is implementable. We run this regression every quarter, as opposed to running it every 6 months as we do in Table 2. We do this to maximize the predictive power of investment.

Table 9
Momentum portfolio returns interacted with expected and unexpected investment.

Panel A. Sorted by predicted investment and past returns

Sorted by predicted investment for half-year +1		Sorted by gross returns for half-year −1: Low returns	2	3	4	High returns
	Low Inv	−0.0071***	−0.0048***	−0.0040***	−0.0036***	−0.0049***
		(−2.85)	(−3.89)	(−4.57)	(−4.41)	(−4.10)
	2	−0.0029	−0.0009	−0.0002	−0.0008	0.0003
		(−1.51)	(−0.89)	(−0.23)	(−1.23)	(0.27)
	3	−0.0028	0.0003	0.0009	0.0006	0.0013
		(−1.59)	(0.27)	(1.26)	(0.89)	(1.49)
	4	−0.0043***	0.0004	0.0020***	0.0023***	0.0034***
		(−2.58)	(0.45)	(2.69)	(3.28)	(3.94)
	High Inv	−0.0049***	−0.0007	0.0020**	0.0042***	0.0060***
		(−3.05)	(−0.73)	(2.38)	(5.27)	(5.31)

Panel B. Sorted by residual investment and past returns

Sorted by residual investment for half-year +1		Sorted by gross returns for half-year −1: Low returns	2	3	4	High returns
	Low Inv	−0.0195***	−0.0129***	−0.0088***	−0.0070***	−0.0071***
		(−8.17)	(−11.57)	(−11.34)	(−9.70)	(−7.33)
	2	−0.0063***	−0.0045***	−0.0025***	−0.0019***	−0.0003
		(−3.35)	(−4.68)	(−3.62)	(−2.83)	(−0.34)
	3	−0.0030	−0.0009	0.0002	0.0005	0.0033***
		(−1.55)	(−0.89)	(0.25)	(0.74)	(3.41)
	4	0.0015	0.0020**	0.0023***	0.0033***	0.0066***
		(0.80)	(2.02)	(3.10)	(4.74)	(6.79)
	High Inv	0.0040**	0.0049***	0.0056***	0.0069***	0.0133***
		(2.05)	(4.94)	(7.65)	(10.77)	(11.49)

This table reports monthly portfolio adjusted returns. The returns are adjusted based on the Fama–French three-factor model. The timing is expressed in 6-month periods, such that half-year -1 refers to half-year before the holding period, and half-year +1 is the holding period. Portfolios are independently sorted on two-way quintiles: the 6-month returns prior to the holding period, and the predicted 6-month asset growth investment contemporaneous to the holding period. Asset growth is predicted using a modified version of regression 4 in Table 2 where asset growth during half year + 1 is predicted using accounting variables (book to market, total assets, return on assets and capital intensity) measured as of period −2, 3 lags of asset growth (Inv(−2), Inv(−3) and Inv(−4)), 4 lags of 6-month returns, and industry dummies. In Panel B, portfolios are independently sorted on two-way quintiles: the 6-month returns prior to the holding period, and the residual values of the predicted 6-month asset growth investment contemporaneous to the holding period. T-statistics are in parentheses, and *** denote significance at the 1% level, ** at the 5% level and * at the 10% level.

value-weighted portfolios. The implications are similar with a value-weighted enhanced spread of 1.23%. This test confirms that the interrelation between investment and past returns is also of interest in capturing the cross-section of returns on an ex-ante basis.[14]

Panel B reports the abnormal returns for portfolios formed using the residual value of predicted investment regression in a two-way sort with past returns. The residual represents the unanticipated investment in Time +1. The notable spread here is that between stocks with high returns and high investment surprises and stocks with low returns and low investment surprises. We find that the momentum spread sorted by unanticipated investment is much larger than that based on the predicted values—investment realization creates large return spreads. The abnormal return is 1.33% (t-stat = 11.49) on the long side and −1.95% (t-stat = −8.17) on the short side, for a long-short spread of 3.28%. Although most of the return effect associated with investment is manifest ex-post (in period +1) with the unanticipated investment, the fact that some of the momentum profits are tradable appears to suggest a market inefficiency. We note that this is not inconsistent with our hypotheses. Our hypothesis is that investment is the channel by which

[14] Nyberg and Poyry's (2014) work complements this observation as they examine momentum effects across various levels of past investment. They find that momentum effects are concentrated among those portfolios with either high or low past investment. Our work makes a similar statement but based on predicted subsequent investment. Although with a different motivation, Hackbarth and Johnson (2015) observe a similar effect with a two-way sort on predicted and past return.

the momentum and reversal effects are manifest. The observation that the market may not fully efficiently price the predictable component of that subsequent investment is not central to our story, but does provide for potential trading opportunities.

4.5. Time-series effects

There is some evidence that the time-series of momentum returns is cyclical in nature. Chordia and Shivakumar (2002) demonstrate that momentum returns are correlated with common macroeconomic variables: aggregate dividend yield, the term premium, the default premium, and short-term interest rates. Cooper et al. (2004) argue that time-series variation in momentum profits is more properly explained by price movements in equity prices; in that momentum profits tend to be concentrated among periods of up markets.

We explore this evidence in light of our proposed investment-based momentum hypothesis. Specifically, we investigate whether our investment-based explanation of momentum is also able to explain momentum in the time-series. To do this we use the monthly winner-less-loser momentum factor available at Ken French's data library. This factor is constructed based on six value-weighted portfolios formed on size and prior (months 2–12) returns. We aggregate the monthly returns into half-year periods following the rest of our paper (January to June and July to December) by summing the monthly returns. We then regress this time-series of non-overlapping six-month period returns on a number of independent variables that are lagged one period so as to not overlap with the dependent variable. These variables include the four Chordia–Shivakumar macroeconomic variables: DIV, the aggregate dividend yield calculated as the sum of dividends for the CRSP value-weighted portfolio over the past 4 quarter dividends divided by current price from Robert Shiller's website (but with monthly interpolation removed to avoid look-ahead bias); TERM, the lagged yield spread between ten-year U.S. Treasury bond yields and 3-month U.S. Treasury yields; DEF, the default premium calculated as the difference between the long-term corporate bond yields of Aaa-rated less Baa-rated bonds; and YLD, the lagged yield on the 30-day U.S. Treasury bill from Ibbotson Associates. Both TERM and DEF are from Ivo Welch's website. TERM, DEF and DIV were obtained through Wayne Ferson and Wayne Chang. YLD is obtained from Kenneth French's data library. All four of these macroeconomic variables are measured the month prior to the beginning of the momentum holding period.

We also include the three series based on past market returns and aggregate investment: MktRet36, the value weighted CRSP total market return cumulated over the prior 36-months following Cooper et al.; UP, a dummy variable that indicates that MktRet36 is positive following Cooper et al.; and AgInv36, average growth in total assets for the previous 36 months. Specifically, we compute the cross-sectional average of the 6 month growth in total assets for all Compustat firms weighted by total assets at the beginning of the period, and sum the time-series of the growth variable over 36 months. We report the results in Table 10.

In the first regression we include the aggregate investment variable as well as DIV, TERM, DEF, and YLD. We observe strong time-series correlation for AgInv36. The positive coefficient is significant at the 5 percent level. The result suggests that past investment provides some predictive power for momentum returns. We also observe significant predictive correlation with TERM and DEF. The nature of momentum profits is predictive in that all of the variables used in the test are known prior to the momentum holding period.

In regression 2 we substitute the past market returns following Cooper, et al. for investment. In this specification we observe positive predictive ability for past market returns but do not observe a significant coefficient on MktRet36. In Regression 3, we include both AgInv36 and MktRet36, as well as an interactive variable. In this specification we observe that while AgInv36 maintains its ability to explain the time-series of momentum returns, MktRet36 does not. Neither the coefficient on MktREt36, nor the interactive term, remain significant. Cooper, et al. emphasize a nonlinear relationship with past market returns. We follow their work by inserting the dummy variable UP in Regression 4. Here we see results that mirror Cooper et al.—the coefficient on UP maintains strong predictive power with a coefficient that is significant at the 1-percent level. In other words, momentum returns are concentrated in periods associated with positive past stock market returns. In regression 5 we add the investment variable AgInv36 and an interactive term. Again we find that the market return variable UP loses its significance. Its only significant explanatory power appears in its interaction with investment.

We conclude that past investment provides some predictive power for the time-series of momentum returns. We provide some evidence that past investment is more important than past returns in explaining momentum.

5. Conclusions

In this paper we explore the momentum and reversal effects in the term structure of stock returns with a proposal that the channel for these patterns is the time delay associated with firms realizing real investments. The intuition is that momentum patterns occur because real investment generates positive investment anticipation and investment realization returns. The total investment–return impact is partially realized with anticipation of the investment and the remaining return coming with the realization of the investment. The decoupling of the realization of the wealth impact of investment is inherent in the time delay associated with real investment. This partitioning of investment returns generates conditional return continuation for both investment and disinvestment. A similar story explains return reversals as investment creates reversal effects in returns with the extended partitioning of the realization periods.

Using a large panel of U.S. stock return and investment data, we confirm these predictions. We document that momentum and reversal in returns do not occur in isolation, but are completely dependent on systematic patterns in firm investment such that there is no residual momentum or reversal effect in stock returns independent of that associated with firm investment. Our evidence is robust to a number of known cross-sectional effects in momentum. We document some opportunities for enhanced trading strategies, but note that most of the momentum effect comes from the unanticipated portions of investment. We also find some evidence that momentum returns are associated with aggregate investment in the time-series.

Table 10
Time-series momentum returns.

	(1)	(2)	(3)	(4)	(5)
Intercept	−4.427	4.414	−7.927	−11.60	−0.797
	(−0.45)	(0.52)	(−0.76)	(−1.11)	(−0.05)
DIV	0.137	−0.627	0.905	−1.960	−1.025
	(0.05)	(−0.21)	(0.29)	(−0.69)	(−0.36)
TERM	4.124**	3.433	3.939*	3.736*	4.769**
	(2.02)	(1.66)	(1.92)	(1.89)	(2.44)
DEF	−19.62***	−16.40***	−17.91***	−11.70**	−14.30***
	(−4.15)	(−3.30)	(−3.62)	(−2.27)	(−2.82)
YLD	1.681	2.223	0.944	2.082	1.114
	(1.13)	(1.48)	(0.59)	(1.53)	(0.78)
AgInv36	70.43**		66.97*		−81.16
	(2.12)		(1.95)		(−0.93)
MktRet36		468.8	348.7		
		(1.33)	(0.67)		
MktRet36 × AgInv36			1937.3		
			(0.24)		
UP				21.69***	−4.702
				(2.76)	(−0.29)
UP × AgInv36					160.5*
					(1.74)
Adj R^2	0.243	0.212	0.240	0.276	0.327

Ordinary least squares time-series regressions use non-overlapping 6 month periods, from January to June and July to December. Half-year returns are the sum of monthly momentum returns obtained from French's data library. All independent variables are lagged 1 period and do not overlap with the dependent variable. MktRet36 is the value weighted returns cumulated 36-months ending the month before we measure momentum. UP is a dummy variable that indicates that MktRet36 is positive following Cooper et al. AgInv36 is the average growth in total assets for the previous 36 months for all Compustat firms weighted by total assets in the previous month. DIV is the aggregate dividend yield calculated as the sum of dividends for the CRSP value-weighted portfolio over the past 4 quarter dividends divided by current price from Robert Shiller's website (but with monthly interpolation removed to avoid look-ahead bias). TERM is the lagged yield spread between ten-year U.S. Treasury bond yields and 3-month U.S. Treasury yields. DEF is the default premium calculated as the difference between the long-term corporate bond yields of Aaa-rated less Baa-rated bonds. YLD is the lagged yield on the 30-day U.S. Treasury bill from Ibbotson Associates and is multiplied by 12 and by 100 to be measured as an annual yield and as a percentage. Both TERM and DEF are from Ivo Welch's website data and were obtained through Wayne Ferson and Wayne Chang. All four of these macroeconomic variables are measured the month prior to the beginning of the momentum holding period. T-statistics are in parentheses, and *** denote significance at the 1% level, ** at the 5% level and * at the 10% level.

In showing that the shape of the term structure in stock returns is inherently due to interactions between investment and returns, we propose important implications for the large literature on the momentum and reversals regularities. In particular we emphasize the need for researchers and market participants to consider the role of anticipated and realized firm investment in understanding momentum and reversal effects on firm equity. A growing literature emphasizes the impact of investment on understanding equity returns (Hou et al., 2015). In general, our paper demonstrates the important impact of the features of investment (e.g., time delay) on such pricing models and suggests future investigation of the features of investment to understand and uncover existing anomalies in security prices.

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