ACCOUNTING & FINANCE

afaanz

Accounting & Finance 58 (2018) 3–43

Dissecting stock price momentum using financial statement analysis

Anwer S. Ahmed[a], Irfan Safdar[b]

[a]*Mays Business School, Texas A & M University, College Station, TX,*
[b]*Widener University, Chester, PA, USA*

Abstract

The literature on stock price momentum documents that past price performance predicts future price performance (over the next 3–12 months). We argue that past price performance can be driven either by fundamentals or by non-fundamental reasons and financial statement analysis (FSA) can help distinguish between these drivers of past returns. We find that price momentum reverses where fundamentals are inconsistent with past price performance, allowing us to develop an investment strategy that outperforms a pure momentum strategy over 80 percent of the time. Overall, we document robust evidence on the usefulness of FSA for enhancing momentum strategies.

Key words: Financial statement analysis; Fundamental analysis; Stock price momentum

JEL classification: G11, G12, G14

doi: 10.1111/acfi.12358

1. Introduction

Stock price momentum typically refers to the continued increase (decrease) in the stock price following a recent increase (decrease) over the past 3–12 months (Jegadeesh and Titman, 1993). It is a puzzling phenomenon because future returns appear to be predictable using past returns, indicating that stock

We gratefully acknowledge helpful comments from Senyo Tse, Lynn Rees, an anonymous referee and workshop participants at Texas A & M University, Rutgers University – Camden, Widener University and University of Akron. We also acknowledge helpful comments from participants at the 2017 Western Region and Southeast Region AAA meeting participants.
Please address correspondence to Irfan Safdar via email: musafdar@widener.edu

market investors do not fully process information in such stocks in a timely fashion. We investigate whether financial statement analysis (FSA) can be used to enhance the performance of momentum-based investing strategies. The potential for FSA to enhance momentum strategies arises because past price changes can be driven either by fundamental or by non-fundamental reasons (such as noise trading). Stocks whose past price performance is driven by non-fundamental reasons should exhibit reversals. There is little evidence in prior research on the extent to which stock price momentum is inconsistent with fundamentals which serves as the primary motivation for our study. If fundamental analysis helps identify these stocks, it can help enhance returns to momentum investing. We document evidence that FSA is useful for enhancing the performance of momentum-based strategies.

Investigating whether FSA enhances returns to momentum investing is important for several reasons. First, while an extensive literature documents that returns to momentum strategies are pervasive, recent studies raise doubts about implementability of momentum strategies, especially in recent periods. Lesmond *et al*. (2004) find that these strategies 'require frequent trading in disproportionately high-cost securities such that trading costs prevent profitable strategy execution'. They conclude that momentum profits are illusory (see also Korajczyk and Sadka, 2004). More recently, Bhattacharya *et al*. (2017) document that returns to momentum strategies are insignificant over the period 1999–2012. If FSA helps to predict the performance of momentum strategies, it could help make them easier to implement and improve performance when pure momentum strategies fail to function as expected.

Second, despite the extensive prior literature on momentum, the sources of momentum profits are not well understood. A potential driver of returns to momentum strategies is risk (Conrad and Kaul, 1998; Berk *et al*., 1999; Johnson, 2002; Liu and Zhang, 2008). Alternatively, momentum returns could reflect mispricing (DeLong *et al*., 1990; Hong and Stein, 1999). Furthermore, some researchers, such as Daniel *et al*. (1998), argue that momentum profits reflect continued overreaction or positive feedback while others theorise that momentum profits reflect underreaction (Barberis *et al*., 1998; Hong and Stein, 1999). While we do not test a specific behavioural theory of momentum, our study sheds light on potential drivers of momentum by showing where momentum is likely to be underreaction or overreaction.

Third, while Piotroski and So (2012) show that FSA helps improve returns to value-glamour strategies due to inconsistency between fundamentals and prices, it is not clear that FSA can be similarly useful in enhancing momentum strategies because it remains unknown whether momentum stocks' prices are inconsistent with fundamentals. Price momentum is distinct from the value/glamour anomaly in that prices appear to continue their performance rather than reverse. Moreover, Fama and French (2008) demonstrate that both momentum and value-glamour anomalies hold after controlling for the other, suggesting they are empirically distinct. In addition, recent work suggests that price and earnings momentum are related. For example, Chordia and Shivakumar (2006) document that the predictive power of past returns overlaps with earnings momentum. Novy-Marx (2015) also concludes that earnings momentum explains price momentum. If past prices are consistent with fundamentals and fully reflect the information in fundamentals, adding signals from FSA may not be useful for momentum strategies.

However, a significant literature following Black (1986) identifies the relevance of noise trading and its potential to drive market prices away from fundamentals (see Shleifer, 2000). The potential for noise trading leaves open the possibility that at least for some momentum-based stocks, prices may have moved contrary to fundamentals. Our essential argument is that the future behaviour of momentum stocks depends upon the degree to which past price performance is consistent with underlying fundamentals. Past price performance can be driven either by (i) fundamentals or by (ii) non-fundamental reasons (i.e. noise trading). If driven by non-fundamental reasons or noise trading, stock price momentum should reverse. A pure momentum strategy combines both types of firms. Therefore, FSA can help enhance momentum strategies in two ways. First, it can identify stocks where past prices are driven by noise and thus are likely to reverse in the future. Excluding these stocks can improve returns to a momentum strategy. Second, FSA can identify firms where past performance is more likely to persist; that is, a firm with strong (weak) fundamentals is likely to exhibit more (less) persistent profitability. Thus, so long as this information is not already reflected in past returns, a combined fundamentals–momentum strategy should yield higher returns than a pure momentum strategy.

In our empirical analysis, we deploy both price momentum and fundamentals-based characteristics using a measure of fundamentals (*F*-score) developed by Piotroski (2000). This measure uses nine binary variables based on financial statement data to assess a firm's fundamentals, including variables based on profitability, liquidity and investment. Although the *F*-score was originally developed to analyse value stocks, recent work has documented its usefulness in identifying mispriced stocks more broadly. For example, Choi and Sias (2012) document that the *F*-score predicts future returns more broadly as well as institutional investor demand. In addition, S&P's Capital IQ database developed for usage by market professionals now regularly provides the *F*-score measure for stocks covered in the database. The prominence of the *F*-score in both academic studies and usage by investment professionals suggests that it is a useful indicator of firm fundamentals and thus can potentially identify price changes driven by non-fundamentals reasons.

We allocate stocks to three momentum groups using the past 6-month returns (dropping stocks below $5/share); terciles 1 (3) are identified as Losers (Winners). As in past studies, we split firms into Strong (*F*-scores 7–9), Medium (4–6) and Weak (0–3) fundamentals-based groups. We merge the momentum rank of a firm to its *F*-score and measure future 6- to 12-month buy-and-hold returns. Using buy-and-hold returns is important in our study because we are interested in whether incorporating fundamentals can prolong the momentum effect, yielding a better strategy. This can reduce transaction costs because portfolios do not need to be rebalanced frequently which is a frequent criticism of momentum-based strategies. It also bypasses microstructure issues such as bid–ask bounce that impact short-horizon returns.

We find that stocks where past price performance is consistent with fundamentals exhibit greater future momentum in a very robust fashion. For example, the average 1-year buy-and-hold return of firms for the 1973–2015 period where past stock price performance is consistent with fundamentals (i.e. Strong Winners–Weak Losers) is 11.59 percent over the year after portfolio formation, compared to 4.35 percent from a pure momentum strategy (Winners–Losers). This indicates that a consistent momentum–fundamentals strategy yields substantially higher returns than a pure momentum strategy for a longer holding period. The effect is remarkably robust in that it generates positive returns 88 percent of the time (37 of 42 years) and outperforms a pure momentum strategy 83 percent of the time (35 of 42 years) (Figure 1). With the exception of the 2008 crisis, the volatility in the strategy is almost entirely due to positive returns.

In addition, we find that in stocks where fundamentals are not consistent with changes in expectations reflected in recent stock returns (i.e. Weak Winners–Strong Losers), there is a reversal of −4.88 percent on average.

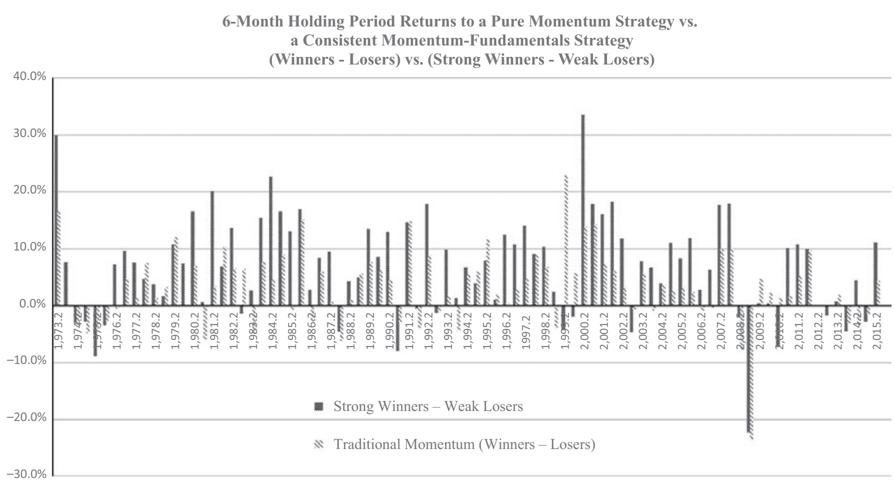


Figure 1 6-Month holding period returns to a pure momentum strategy vs. a consistent momentum-fundamentals strategy (Winners – Losers) vs. (Strong Winners – Weak Losers). A comparison of 6-month holding-period returns of portfolios formed in January and June based on pure price–momentum categories and portfolios formed based on consistency in momentum and fundamentals. Sample: 1973–2015.

Overall, the ex-post-Sharpe ratio of a 6-month holding-period strategy based on consistency between past stock price performance and fundamentals is 50 percent greater than that of a pure momentum strategy. These findings are robust to dropping microcaps (bottom two NYSE-based capitalisation deciles) and to controlling for more extreme momentum stocks. They are also robust to controls for market, size and book-to-market (b/m) factors. Furthermore, they are robust to controlling for interaction between momentum and earnings surprises (SUE), interaction between momentum and b/m, interaction between fundamentals and b/m and interaction between momentum and gross profitability. They are also robust to using quintiles or deciles-based momentum ranks.

We contribute to the literature on the usefulness of FSA by examining its relation to momentum investing in a number of ways. First, our study examines whether FSA is still useful if prices are consistent with fundamentals. While Piotroski and So (2012) demonstrate that FSA can be used to identify expectational errors in value and glamour stocks, our study provides evidence on whether FSA can identify expectational errors in momentum stocks, an anomaly conceptually and empirically distinct from value and glamour (Fama and French, 2008). Second, some researchers raise questions about implementability of momentum strategies as well as the existence of momentum profits in recent periods. We find that incorporating FSA into momentum increases returns, reduces downside risks and reduces trading requirements. Furthermore, we find that the combined fundamentals–momentum strategy yields significant risk-adjusted returns even in recent periods whereas recent research shows that traditional momentum strategies are much weaker in performance during these periods. These findings are useful for delivering consistent performance to momentum investors. Third, consistent with our stock return results, we also find that analyst forecast revisions exhibit a similar pattern. In other words, analyst revisions are greater for firms that have past price performance consistent with fundamentals than for firms that have past prices performance inconsistent with fundamentals. This indicates an error in expectations similar to investors.

Finally, our findings shed light on potential sources of momentum. They suggest that momentum is unlikely to be driven by risk because returns to momentum are higher for firms where past performance is consistent with fundamentals. In other words, the high (low) returns to Strong Winners (Weak Losers) are unlikely to be driven by risk because firms with strong (weak) fundamentals are unlikely to be more (less) risky firms. In addition, our results highlight an important insight about the behaviour of momentum stocks. Whether momentum reflects underreaction or overreaction cannot be discerned without disentangling the relation between prices and fundamentals. In other words, stocks in momentum portfolios can reflect trading that is either consistent or inconsistent with fundamentals. Our study shows that both types of trading are present which determines the future performance of momentum stocks.

In the remainder of the paper, Section 2 discusses relevant literature and background. Section 3 discusses data and empirical methods. Section 4 discusses empirical results. Section 5 concludes.

2. Background and hypothesis development

The momentum literature is vast, and there are a number of useful literature reviews (e.g. Jegadeesh and Titman, 2011). Below, we discuss some prior studies from both the momentum literature and the FSA literature that are most relevant to our study. We then discuss our hypothesis.

2.1. Stock price momentum

The momentum effect was identified by Jegadeesh and Titman (1993) who found that stock price performance over the past 3–12 months predicts stock returns in the next 3–12 months. An extensive literature followed to explain this phenomenon. Follow-up studies show that the behaviour is pervasive in not only US markets but also in international markets (Asness *et al*., 2013). The primary explanations of the momentum effect revolve around risk-based theories or investor biases. The risk-based explanation posits in some sense that higher (lower) ex-post returns are a compensation for higher (lower) risk (Conrad and Kaul, 1998). Jegadeesh and Titman (2001) argue that such a theory implies that cross-sectional differences in momentum should continue in the long run and can be rejected if momentum halts or reverses. They find that momentum returns do not continue indefinitely and may reverse in some periods.

Several studies examine whether momentum profits can be explained by exposures to systematic or business cycle risk factors. This argument relies on asset pricing theories which suggest that covariance with marginal utility of consumption (or production) as captured by systematic risk factors is higher for winners than losers; that is, the undiversifiable risk of past winners is higher and therefore a higher return is required of these stocks compared to losers. In empirical work, Chordia and Shivakumar (2002) find that momentum profits are generally predictable based on exposures to several macroeconomic variables. However, Griffin *et al*. (2003) report that this result does not hold in several international markets. More importantly, they find that in more direct asset pricing tests, exposures to macroeconomic variables fail to explain momentum. More recently, Asness *et al*. (2013) find only a modest link between momentum and global macroeconomic factors. Liu and Zhang (2008) also find that a production-based risk factor fails to explain most of the momentum effect.

In the absence of a satisfying risk-based explanation, several studies explore behavioural explanations for momentum. These explanations view momentum as either underreaction or overreaction to information. Both types of reaction are modelled in a number of behavioural models that rely on different types of psychological biases to generate a theoretical basis for price behaviour (Barberis *et al*., 1998; Daniel *et al*., 1998; Hong and Stein, 1999). To our knowledge, tests of these models do not find conclusive evidence that any particular model succeeds in providing a complete explanation for stock price momentum. Nonetheless, empirically it appears that institutional investors are active in momentum stocks (Grinblatt *et al*., 1995; Nofsinger and Sias, 1999) which lends credibility to the notion of professional investors taking advantage of potential mispricing. However, this result seems to be specific to certain types of institutions (Badrinath and Wahal, 2002) and does not provide clarification on the mechanism by which momentum presents a trading opportunity for some institutional investors.

A number of studies also examine whether momentum profits can be explained using firm characteristics. Stock price momentum appears to be stronger in stocks with higher volatility (Sagi and Seasholes, 2007; Hou *et al*., 2009) and lower credit ratings (Avramov *et al*., 2007). Asness (1997) and Daniel and Titman (1999) report that momentum is stronger in growth (low b/m) stocks. Furthermore, Zhang (2006) and Verardo (2009) find that information uncertainty measured by analyst forecast dispersion is linked to momentum effects. However, a recent study by Bandarchuk and Hilscher (2012) finds that the link between each of these characteristics and momentum is due to selecting stocks with more extreme past returns. Controlling for extreme momentum, they show that there is little link between momentum and these characteristics.

An important question with respect to momentum investing strategies is whether they generate sufficient returns to cover their transaction costs. Lesmond *et al*. (2004) find that momentum is located in firms that have very high trading costs. They conclude that momentum profits are illusory. In addition, Bhattacharya *et al*. (2017) document that momentum strategies are no longer profitable in recent periods (1999–2012). In other words, the momentum effect seems to have faded and momentum-based investing strategies may no longer be worth pursuing.

2.2. Financial statement analysis

While momentum-based strategies rely exclusively upon past price patterns, FSA-based strategies rely on the ability of financial statement data to predict stock returns. Investment strategies based on fundamentals that can typically be gleaned from financial statements go at least as far back as Graham and Dodd (1934). Accounting research began systematically investigating the usefulness of financial signals in the 1980s. Ou and Penman (1989a,b) show that financial ratios predict future earnings and returns. Abarbanell and Bushee

(1997, 1998) show that a subset of signals developed by Lev and Thiagarajan (1993) predict future earnings changes and abnormal returns. Piotroski (2000) uses a summary measure based on financial statement data to identify more attractive value stocks in a sample of high book-to-market firms while Mohanram (2005) uses a refined measure of fundamentals called the G-score to identify more attractive growth stocks (low book-to-market firms). More recently, Piotroski and So (2012) show that the value/glamour effect exists in firms where the price signals in book-to-market are inconsistent with underlying fundamentals.[1]

A concurrent working paper (Huang *et al*., 2017) derives a measure of momentum in 'fundamentals' based on trends in several financial statement variables such as profitability and liquidity (similar to the *F*-score). They show that their measure is independent of stock price momentum and use combined price and fundamentals-based momentum to derive higher returns to a momentum strategy. Their study does not consider the extent to which the behaviour of momentum stocks is consistent or inconsistent with fundamentals as our study does. Furthermore, we report longer horizon returns based on momentum and fundamentals whereas they do not. Finally, we also examine whether analyst revisions exhibit a similar pattern as stock returns whereas their study does not examine analyst behaviour.

2.3. Noise trading

Black (1986) identifies noise traders as traders or investors who trade based on information unrelated to fundamentals. Since Black (1986), noise trading has become an important foundation for motivating mispricing theories (Shleifer, 2000). Yet, there is little evidence whether prices of momentum stocks are affected by noise trading. In a perfectly efficient market, noise traders' activities should not be able to drive prices far from fundamentals because rational arbitrageurs would counteract price movements induced by noise trading, diminishing price volatility caused by noise trading. However, both theoretical and empirical behavioural finance literatures suggest that noise trading can have a significant and prolonged effect on stock prices. Prominent real-world examples in recent memory include the Internet bubble at the turn of the century and the recent US housing bubble where prices were driven to extremes despite that fundamentals did not appear to support prices. These examples suggest that price bubbles can form and persist for some time in markets and are likely reasons that explanations based on noise trading have gained credence in the market efficiency debate.

[1] Choi and Sias (2012) provide additional credibility to the *F*-score as an important measure of fundamentals by confirming that sophisticated investors trade in stocks identified based on the *F*-score and appear to do so at the expense of individual investors.

Formal models of noise trading discuss potential mechanisms by which noise trading can have a prolonged effect before prices revert to fundamentals (DeLong *et al*., 1990; Shleifer and Vishny, 1997; Mendel and Shleifer, 2012). First, noise traders can act in a coordinated fashion to trigger price movements (initiated either by chance or in response to some common signal that they deem value-relevant).[2] Once a price movement ensues, rational traders (or arbitrageurs) face two choices. They can trade against it and help correct prices by engaging in risky arbitrage (stock prices do not have perfect substitutes)[3] or take advantage of the trend in anticipation of the bubble becoming larger, known as positive-feedback trading. In some models, the latter is considered rational if prices are expected to continue the trend (Mendel and Shleifer, 2012). Price-watching irrational traders may also attempt to chase the trend, exerting further pressure on prices. Therefore, both irrational and rational trading can feed a bubble triggered by noise trading, decoupling prices from fundamentals. The important idea is that prices are not being driven by fundamentals in these cases. The Internet and housing bubbles are examples of how this can create trends in divergence from fundamentals that do not correct themselves quickly. We believe that similar trends can take hold in at least *some* momentum stocks due to noise trading. This argument is consistent with both empirical observation and noise trading theory.

In principle, noise traders are irrational actors because their expectations are not based on fundamentals. In some well-known behavioural models such as Barberis *et al*. (1998) and Daniel *et al*. (1998), noise trading exists due to inaccurate extrapolation of past trends or due to overconfidence. However, the nascent noise trading literature typically does not identify biases that drive these trends. In our study, as in much of this literature, we do not take a position on what type of specific behavioural biases drive noise trading. Instead, we rely on the essential notion that prices can diverge from fundamentals in cases where noise trading prevails. Given that momentum stocks reflect extreme changes in

[2] Examples of signals include following prominent television personalities, investment gurus, investment articles or other commonly available social media (Reddit.com is a modern example). Black (1986) notes that noise traders may believe that they are trading on information that is only noise in hopes of gaining an edge over the market. Kumar and Lee (2006) and Barber *et al*. (2008, 2009) document empirical evidence of correlated trading patterns amongst uninformed investors.

[3] In markets without perfect substitutes or definite expiration, arbitrage is considered limited and risky. When perfect substitutes exist, the arbitrageur can lock in an immediate profit because prices must converge to fundamentals as the derivative security expires (e.g. options and futures contracts). Stock prices have a substantial idiosyncratic component, disallowing perfect substitutes, and have no expiration. Because their positions are not fully hedged, arbitrageurs face the risk that fundamentals may change before expected profits are realised, implying that they cannot lock in profits (Shleifer and Summers, 1990). They must answer to providers of capital should prices diverge from expectations, potentially facing liquidation before prices converge to fundamentals (Shleifer and Vishny, 1997).

prices, whether the prices of momentum stocks can be substantially driven away from fundamentals is an empirical question.

2.4. Central hypothesis

The noise trader literature in finance suggests that past price changes may be driven by either fundamentals or non-fundamental reasons.[4] We expect price changes driven by noise to eventually reverse. On the other hand, price changes that are consistent with fundamentals are less likely to reverse. Moreover, if the price changes are driven by underreaction to fundamentals, prices should continue to move in the same direction until the information is fully reflected in stock prices. A pure momentum strategy includes both types of stocks (fundamental and noise-related). Financial statement analysis is a potential means of separating fundamental-driven trades from noise-driven trades. Thus, we expect that identifying stocks where trading is noise-driven helps distinguish firms where the momentum effect is more likely to be stronger and prolonged. This leads to our central hypothesis:

H1: The momentum effect is stronger when expectations about a firm's performance reflected in past prices are consistent with fundamentals.

3. Data and research design

3.1. Sample

The sample for this study spans the period 1973–2015 using the intersection of CRSP and Compustat. The data requirements are financial statement data to compute the *F*-score and at least 6 monthly stock returns to compute momentum. If a stock becomes delisted, we assign its delisting return as its last monthly return. Momentum-based ranks are assigned using all available CRSP firms with stock return data. As in earlier studies (e.g. Jegadeesh and Titman, 2001), we allocate firms to momentum-based categories using the 6-month lagged stock return calculated by skipping the current month. Prior to assigning momentum ranks, we drop firms whose stock price is below $5 per share as is typical in the literature (Jegadeesh and Titman, 2001). Using annual financial statement data, we calculate an *F*-score for each firm as a summary measure of financial statement fundamentals based on Piotroski (2000), described in Appendix. We drop financial institutions (SIC codes 6,000–6,999). Merging momentum ranks and *F*-score s yields 93,271 unique firm-year observations.

---

[4] O'Hara (2003) stresses the importance of viewing trading as a product of interaction between informed and uninformed investors (see also Grossman and Stiglitz, 1980; Black, 1986; Shleifer, 2000).

3.2. Momentum- and fundamentals-based categories

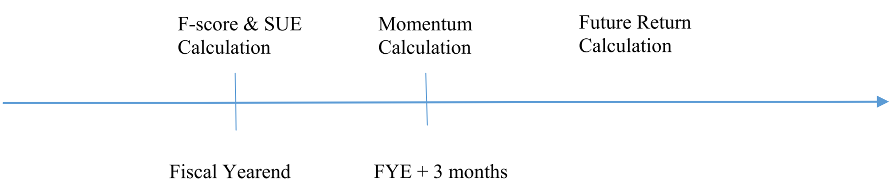
Momentum ranks are updated once a year as of 3 months after fiscal year-end. We allocate firms into the following groups based on the firms' past 6-month returns as of 3 months after fiscal year-end:

Winners = stocks in tercile three based on lagged 6-month returns
Losers = stocks in tercile one based on lagged 6-month returns
Extreme Winners = stocks in decile 10 based on lagged 6-month returns
Extreme Losers = stocks in decile one based on lagged 6-month returns

We attach the firm's *F*-score using annual financial statement data as of the recent fiscal year-end. We form three fundamental-based categories using the *F*-score as in earlier studies (Piotroski, 2000; Piotroski and So, 2012): 1) *strong* = firms with *F*-score s of 7–9, 2), *medium* = firms with *F*-score s of 4–6 and 3) *Weak* = firms with *F*-scores of 0–3.

For sensitivity and robustness tests, we also require a firm's quarterly earnings surprise (SUE). For each firm, we calculate and attach the earnings surprise (SUE) as the seasonal change in quarterly earnings scaled by average total assets for the 4th fiscal quarter. We allocate firms to SUE-based categories using all firms whose fiscal year-ends during the past 3 months (Sadka, 2006). We calculate the future buy-and-hold return of each firm starting in the 4th month after fiscal year-end.

The diagram below illustrates formation of the categories described above.



Because firms can have different fiscal year-ends, we first analyse the behaviour of momentum stocks in event time (i.e. relative to fiscal year-end) as described above. In the latter part of the paper (Table 7), we simulate the behaviour of an investment strategy implementable in calendar time. Details of portfolio formation for the strategy accompany the analysis in Section 4.

3.3. Sample descriptive statistics

Table 1 provides descriptive statistics for both Strong and Weak fundamentals-based categories within each momentum tercile along with descriptive statistics for the full sample for comparison. The sample excludes stocks with prices below $5/share and financial institutions. We provide descriptive

Table 1
Sample descriptive statistics

Sample Period: 1973–2015

		Winners			Med Mom			Losers		
	Full sample	All Winners	Strong	Weak	All Med Mom	Strong	Weak	All Losers	Strong	Weak
MVE ($mil.)	$3,185	$3,045	$2,947	$1,640	$3,701	$3,820	$2,145	$2,875	$3,219	$1,466
BM	0.68	0.61	0.70	0.52	0.71	0.76	0.67	0.71	0.75	0.67
ROA	5.22%	5.42%	8.51%	−7.59%	6.13%	7.95%	−2.28%	4.22%	8.10%	−5.71%
ΔROA	−0.05%	0.97%	4.60%	−8.47%	0.01%	3.14%	−6.52%	−1.11%	4.03%	−8.87%
CFO	10.7%	11.1%	15.1%	−2.1%	11.4%	13.9%	1.9%	9.6%	14.3%	−0.9%
Accrual	−5.16%	−5.39%	−6.18%	−5.21%	−5.02%	−5.71%	−4.09%	−5.05%	−5.87%	−4.39%
ΔTurn	−1.34%	0.24%	9.10%	−11.6%	−1.47%	6.89%	−11.5%	−2.81%	7.74%	−12.6%
ΔMargin	0.30%	0.96%	2.80%	−10.57%	0.27%	2.08%	−6.64%	−0.32%	2.51%	−10.12%
ΔLever	0.06%	−0.25%	−2.75%	3.52%	−0.02%	−2.21%	3.24%	0.45%	−2.56%	3.66%
ΔLiquid	−2.83%	−3.70%	13.7%	−55.4%	−2.20%	12.7%	−46.3%	−2.52%	18.6%	−49.7%
Issuance	5.79%	6.15%	3.91%	12.6%	4.50%	3.10%	9.14%	6.55%	4.57%	11.0%
F-score	5.4	5.5	7.4	2.5	5.5	7.4	2.7	5.1	7.4	2.5
Fiscal Year-end SUE	0.20%	0.76%	1.65%	−1.62%	0.23%	1.04%	−1.63%	−0.37%	1.13%	−2.80%
Momentum Decile	5.5	8.80	8.83	8.92	5.52	5.55	5.48	2.15	2.31	1.89
Past 6-month Return	11.0%	40.7%	38.4%	56.1%	6.8%	6.8%	6.6%	−15.0%	−12.3%	−19.8%
Analyst Revisions[†]	−0.12%	−0.05%	0.01%	−0.18%	−0.10%	−0.03%	−0.24%	−0.22%	−0.11%	−0.40%

(continued)

Table 1 (continued)

Sample Period: 1973–2015

		Winners			Med Mom			Losers		
	Full sample	All Winners	Strong	Weak	All Med Mom	Strong	Weak	All Losers	Strong	Weak
Avg. Firms/Year	2,221	864	266	95	735	206	70	844	172	138
No. of annual periods	42	42	42	42	42	42	42	42	42	42
Firm-Year Obs	93,271	32,367	9,741	3,522	28,364	7,836	2,723	32,540	6,551	5,363

This table reports descriptive statistics for the full sample and three stock price momentum categories based on past 6-month stock returns. The 6-month stock return is calculated as of 3 months after fiscal year-end of the firm. The *F*-score is a measure of fundamentals based on financial statement data. *F*-scores range between 0 and 9. Stocks with *F*-scores 0–3 are classified as Weak and *F*-scores 7–9 are classified as Strong. *F*-score calculation is described in detail in the Appendix. MVE is market value of equity ($millions) calculated as the fiscal year-end price times the shares outstanding. The book-to-market ratio is the ratio of total common equity (Compustat item CEQ) divided by MVE. SUE is defined the seasonal change in quarterly net income calculated at fiscal year-end and scaled by average total balance sheet assets. The momentum decile is the average decile of momentum-based deciles. The remaining variables are defined in the Appendix. Analyst revision is calculated as the difference between the last consensus estimate for a firm's quarterly earnings before announcement and the last consensus estimate prior to the fiscal year-end at which the *F*-score is calculated. †Winsorised at 1 and 99 percent.

statistics for several characteristics including size, book-to-market, momentum, and SUE along with other financial statement data used to compute the *F*-score. We discuss notable highlights from Table 1. Some of these observations motivate robustness tests later in the paper.

The average *F*-score is generally similar for momentum-based Winners and Losers, which indicates that there are both Strong and Weak firms amongst both Winners and Losers. There are both Strong and Weak firms amongst Winners (253 and 90 on average, respectively) and losers (166 vs 132, respectively). This suggests that Winners are not uniformly Strong and Losers are not uniformly Weak, indicating the potential for conflict between expectations reflected in recent stock price momentum and fundamentals within the Winner and Loser categories. This is consistent with the central thesis of this paper that the subsequent behaviour of momentum stocks within Winner and Loser categories is likely to depend on the degree of consistency with fundamentals.

Table 1 provides statistics on the past 6-month return used to form momentum categories. Weak Winners have greater past returns (56.1 percent average) than Strong Winners (38.4 percent average). However, the momentum decile of the former (8.92) is only slightly greater than the latter (8.83). This suggests that sorting Winners into Strong vs. Weak firms does not select firms with extreme momentum. Furthermore, the difference in average momentum decile of Strong Winners and Weak Losers [= 8.83–1.89] is only 0.28 deciles greater than the difference in average decile of Winners and Losers from the pure momentum strategy [= 8.80–2.15]. This suggests that sorting on fundamentals does not lead to extreme momentum stocks. Nonetheless, our tests in Table 3 of the paper include controls for extreme momentum using momentum-based deciles.

4. Empirical tests and results

4.1. Size-adjusted returns to stock price momentum and fundamentals-based portfolios

Table 2 presents time series means of average size-adjusted 12-month buy-and-hold returns for three momentum and three fundamentals-based portfolios over the sample period 1973–2015. Terciles 1, 2 and 3 based on the past 6-month return are defined as Losers, Med-momentum and Winners, respectively. We calculate the future buy-and-hold size-adjusted return of each firm as either the 6- or 12-month return starting 4 months after fiscal year-end minus the contemporaneous return of a size-matched portfolio using NYSE-based market capitalisation breakpoints.

We calculate the mean size-adjusted stock return of each momentum rank each period and report the time series average returns along with *t*-statistics in Table 2. A total of 42 12-month periods are available for the sample 1973–

Table 2
Average size-adjusted returns to categories based on stock price momentum and fundamentals

		Winners	Losers	Winners - Losers	No. of periods
	Mean Ret	3.01%	−1.34%	4.35%	42
	T-stat	*2.77*	*−1.25*	*2.29*	
	Avg Firms/Year	864	844		
Strong F (7–9)	3.84%	5.17%	1.84%	3.33%	42
T-stat	*4.51*	*4.34*	*1.52*	*1.85*	
Avg Firms/Year	644	266	172		
Mid-F (4–6)	0.66%	2.37%	−1.32%	3.69%	42
T-stat	*1.25*	*2.18*	*−1.18*	*1.91*	
Avg Firms/Year	1495	504	533		
Weak F (0–3)	−4.75%	−3.04%	−6.43%	3.38%	42
T-stat	*−4.00*	*−1.43*	*−4.16*	*1.35*	
Avg Firms/Year	303	95	138		
Strong - Weak	8.59%	8.21%	8.26%		
T-stat	*5.03*	*3.24*	*5.09*		
			Tests		
	Inconsistent Momentum and Fundamentals				
	Winners × Weak - Losers × Strong		−4.88%		
	T-statistic		−1.68		
	Consistent Momentum and Fundamentals				
	Winners × Strong - Losers × Weak		11.59%		
	T-statistic		4.74		

This table reports time series means of average size-adjusted annual returns for three momentum and three fundamentals-based categories over the sample period 1973–2015. We assign momentum terciles as of 3 months after fiscal year-end using the past 6-month return (skipping the current month) and drop firms with stock prices below \$5/share. Terciles 1, 2 and 3 based on the past 6-month return are assigned as Losers, Med-momentum and Winners, respectively. For each firm, we calculate an annual buy-and-hold size-adjusted return of each firm, calculated as the 6-month return starting 4 months after fiscal year-end minus the 12-month return of a size-matched portfolio using NYSE-based market capitalisations. To calculate the buy-and-hold return of a firm, we assign the delisting return of the firm as the last monthly return of the firm and assume zero return for the remaining holding period if the firm has fewer than 12 monthly returns available. We calculate the mean size-adjusted stock return of each momentum tercile by calendar year and then report the time series average for each momentum-based category along with the associated *t*-statistic in the table.

To create fundamentals-based categories, we assign firms with *F*-scores of 0–3, 4–6 and 7–9 to the 'Weak', 'Mid-F' and 'Strong' categories, respectively. *F*-score is a summary measure of fundamentals based on data obtained from a firm's financial statements. Details of

calculating F-scores are provided in the Appendix. For each firm, we calculate the mean 12-month future size-adjusted buy-and-hold return starting 4 months after fiscal year-end, as described above. We calculate the mean annual size-adjusted stock return of each fundamentals-based category by calendar year and then take the time series average for each category which is reported along with the t-statistic.
The table also reports mean returns for categories based on the interaction between the momentum and fundamentals-based categories. Under 'Tests', the table reports the time series mean of difference in returns of momentum categories based on consistency between fundamentals and momentum. The 'Inconsistency' test reports the difference in returns of 'Winners' with 'Weak' fundamentals and 'Losers' with 'Strong' fundamentals. The 'Consistent' test reports the difference in returns of 'Winners' with 'Strong' fundamentals and 'Losers' with 'Weak' fundamentals. The table also reports the average number of firms available per period in each category.

2015. Confirming past studies, Winners (tercile 3) outperform Losers (tercile 1) by 4.35 percent per year (t-statistic 2.29). This effect is smaller than previous studies for two reasons. First, we use terciles to retain a higher number of firms in momentum × fundamentals-based interaction categories rather than deciles. Second, momentum is often examined at the 1-month horizon because it tends to fade beyond that. One of the goals of this study was to illustrate that the effect can be prolonged based on consistency with fundamentals which would reduce the portfolio turnover required to implement an investment strategy. Therefore, we examine longer horizon buy-and-hold returns. Nonetheless, the essential effects discussed in this study are easily duplicated using quintiles or deciles of momentum and at shorter time horizons. The table also reports the average number of firms available per period in each category.

To create fundamentals-based categories, we assign firms with F-scores of 0–3, 4–6 and 7–9 to the 'Weak', 'Mid-F' and 'Strong' categories, respectively. Details of calculating F-scores are provided in the Appendix. For each firm, we then calculate the 1-year future size-adjusted buy-and-hold return starting 4 months after fiscal year-end, as described above. We calculate the mean annual size-adjusted stock return of each fundamentals-based category by calendar year and then take the time series average which is reported along with the t-statistic. Confirming past studies, Strong firms outperform Weak firms by 8.59 percent per year (t-statistic 5.03).

The table also reports mean returns for categories based on the interaction between the momentum- and fundamentals-based categories. There are two notable observations. First, Winners have a sized-adjusted return of 5.17 percent (t-statistic 4.34) when the fundamentals are Strong and −3.04 percent (t-statistic −1.43) when fundamentals are weak. Second, Losers exhibit a return of 1.84 percent (t-statistic 1.52) when fundamentals are Strong and −6.43 percent (t-statistic −4.16) when fundamentals are weak. This provides initial evidence in support of the central argument of this paper that the momentum effect is a function of the degree to which prior stock returns are consistent or inconsistent with financial statement fundamentals.

Under ‘tests’, the table reports the time series mean of difference in returns of momentum categories based on consistency between fundamentals and momentum. The ‘Consistent’ test reports the difference in returns of Strong Winners and Weak Losers. This difference is 11.59 percent per year (*t*-statistic 4.74) which is significantly greater than returns to the pure momentum strategy. Meanwhile, the ‘Inconsistent’ test reports the difference in returns of Weak Winners and Strong Losers; it is −4.88 percent (*t*-statistic of −1.68), which is indicative of a reversal in the momentum effect.

4.2. Regression tests based on consistency between stock price momentum and fundamentals with controls for size, book-to-market and extreme momentum

Table 3 provides the primary evidence on the central hypothesis of the paper. We regress future returns on dummy variables based on interaction between stock price momentum and fundamentals using cross-sectional Fama-Macbeth type regressions (Fama and MacBeth, 1973) while controlling for a number of factors. The dependent variable in each regression is the firm’s future buy-and-hold return. Independent variables include dummy variables assigned as described below using stock price momentum and fundamentals-based categories as described in Section 3.2. The following cross-sectional regression is estimated each period using all firms with fiscal year-ends in the same calendar year:

$$\begin{aligned} R_{t+1,i} = a_{0,t} &+ a_{1,t} * Winners_{t,i} + a_{2,t} * Winners \times MidFscore_{t,i} \\ &+ a_{3,t} * Winners \times Strong_{t,i} + a_{4,t} * MedMom \times Strong_{t,i} \\ &+ a_{5,t} * MedMom \times Weak_{t,i} + a_{6,t} * Losers_{t,i} + a_{7,t} * Losers \\ &\times MidFscore_{t,i} + a_{8,t} * Losers \times Weak_{t,i} \\ &+ b_{1,t} * Extreme\ Winners_{t,i} + b_{2,t} * Extreme\ Losers_{t,i} \\ &+ c_{1,t} * Sizerank_{t,i} + c_{2,t} * BMrank_{t,i} + e_{t,i} \end{aligned}, \quad (1)$$

where, $R_{t+1,i}$–future 6- or 12-month buy-and-hold stock return of firm i beginning 4 months after fiscal year-end, $Winners_{t,i}$–dummy variable = 1 if the firm falls into momentum tercile 3 as of 3 months after fiscal year-end and 0 otherwise, $MedMom_{t,i}$–dummy variable = 1 if the firm falls into momentum tercile 2 as of 3 months after fiscal year-end and 0 otherwise, $Losers_{t,i}$–dummy variable = 1 if the firm falls into momentum tercile 1 as of 3 months after fiscal year-end and 0 otherwise, $Strong_{t,i}$–dummy variable = 1 if the firm falls into a Strong fundamentals category (*F*-scores 7–9) and 0 otherwise, $MidFscore_{t,i}$–dummy variable = 1 if the firm falls into a medium fundamentals category (*F*-scores 4–6) and 0 otherwise, $Weak_{t,i}$–dummy variable = 1 if the firm falls into a Weak fundamentals category (*F*-scores 0–3) and 0 otherwise, $Extreme\ Winners_{t,i}$–dummy variable = 1 if the firm falls into decile 10 based on its

Table 3
Fama-Macbeth regressions of future buy & hold stock returns to stock price momentum and fundamentals-based categories

	t+6 Months			*t*+12 Months	Year *t*+2	Year *t*+3
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	5.14%	5.3%	5.19%	13.2%	15.1%	15.95%
	2.83	*2.99*	*2.98*	*4.28*	*4.57*	*4.69*
Winners	1.44%	−2.97%	−3.78%	−5.99%	−2.12%	0.27%
	2.25	*−1.95*	*−2.68*	*−2.73*	*−0.95*	*0.13*
Winners × Mid-*F*-score		4.03%	4.14%	6.52%	1.44%	0.73%
		3.07	*3.17*	*3.72*	*0.67*	*0.39*
Winners × Strong		6.26%	6.34%	9.59%	3.65%	1.25%
		3.93	*4.00*	*3.70*	*1.43*	*0.53*
Med Mom × Strong		1.06%	1.06%	2.35%	1.17%	0.74%
		1.80	*1.79*	*2.91*	*1.68*	*1.14*
Med Mom × Weak		−2.96%	−2.94%	−5.77%	−3.43%	−1.29%
		−4.02	*−3.97*	*−3.99*	*−2.04*	*−0.76*
Losers	−1.85%	0.19%	0.57%	1.80%	2.58%	0.00%
	−2.32	*0.27*	*1.04*	*2.22*	*2.48*	*0.00*
Losers × Mid-*F*-score		−1.85%	−1.63%	−3.2%	−1.0%	0.41%
		−4.24	*−3.69*	*−3.83*	*−1.27*	*0.41*
Losers × Weak		−5.58%	−4.97%	−8.37%	−2.86%	0.83%
		−6.49	*−6.25*	*−5.75*	*−1.61*	*0.38*
Extreme Losers (Decile 1)			2.51%	2.73%	−0.89%	−0.80%
			2.72	*1.56*	*−0.64*	*−0.80*
Extreme Losers (Decile 1)			−1.95%	−3.18%	1.43%	0.59%
			−1.60	*−1.78*	*1.04*	*0.39*
Decile (Mktval)	−0.09%	−0.13%	−0.10%	−0.27%	−0.33%	−0.36%
	−0.78		*−0.88*	*−1.24*	*−1.40*	*−1.56*
Decile (Btom)	0.28%	0.26%	0.27%	0.83%	0.70%	0.59%
	2.15		*2.09*	*2.80*	*2.26*	*1.90*
Avg. # of Firms	2366	2360	2358	2415	2284	2154
Avg. Adj. R^2	2.18%	2.95%	3.52%	4.35%	3.28%	3.14%
Coefficient tests						
1. Winners - Losers	3.29%	−3.16%	−4.35%	−7.79%	−4.71%	0.27%
	2.82	*−2.05*	*−3.13*	*−3.13*	*−2.27*	*0.12*
2. Consistent Momentum &		8.68%	6.96%	10.17%	1.81%	0.69%
Fundamentals		*4.95*	*4.87*	*5.08*	*0.79*	*0.28*

T-statistics in italics. This table reports time series means of coefficients from Fama-Macbeth type regressions for the sample 1973–2015. The dependent variable in each regression is firm level future buy-and-hold 6- or 12-month stock return. The 6-month returns are measured starting 4 and 10 months after fiscal year-end. The 12-month stock return is measured starting 4 months after fiscal year-end for up to 3 years in the future. In models 1–3, the dependent variable is the 6-month return for months 4–9 and 10–15 after fiscal year-end. In models 4–6, the dependent variable is the 12-month return for months 4–15, 16 to 27 and 28–39 after fiscal year-end. Independent variables include dummy variables as described in Appendix based on momentum-based and fundamentals-based categories assigned in notes to

panel A of Table 2. The momentum tercile of each firm is identified as of 3 months after fiscal year-end. Fundamentals measures are described in notes to Table 2. We also control for returns to extreme winners and losers defined as portfolios of firms based on deciles 1 and 10 based on past stock price momentum. Firms with stock prices below $5/share as of momentum formation are excluded.
The following cross-sectional regression is estimated each period using all firms with data available on their momentum and fundamentals-based characteristics:

$$\begin{aligned} R_{t+1,i} = {} & a_{0,t} + a_{1,t} * Winners_{t,i} + a_{2,t} * Winners \times MidFscore_{t,i} + a_{3,t} * Winners \times Strong_{t,i} \\ & + a_{4,t} * MedMom \times Strong_{t,i} + a_{5,t} * MedMom \times Weak_{t,i} \\ & + a_{6,t} * Losers_{t,i} + a_{7,t} * Losers \times MidFscore_{t,i} + a_{8,t} * Losers \times Weak_{t,i} \\ & + b_{1,t} * Extreme\ Winners_{t,i} + b_{2,t} * Extreme\ Losers_{t,i} \\ & + c_{1,t} * Sizerank_{t,i} + c_{2,t} * BMrank_{t,i} + e_{t,i} \end{aligned}$$

All variables are described in the Appendix.
The table reports time series means of coefficients with associated Fama-Macbeth t-statistics. The table also reports the average number of firms used in the annual regressions. The first coefficient test reports a test of the differences in returns of firms in momentum-based Winners and Losers categories. The second test reports a test of the difference in average returns of firms based on consistency between stock price momentum and fundamentals defined as:

$$[\text{Winners} + \text{Winners} \times \text{Strong}] - [\text{Losers} + \text{Losers} \times \text{Weak}]$$

past 6-month stock return and 0 otherwise, $Extreme\ Losers_{t,i}$–dummy variable = 1 if the firm falls into decile 1 based on its past 6-month stock return and 0 otherwise, $Sizerank_{t,i}$–the NYSE-based size decile of the firm from the most recent calendar year, $BMrank_{t,i}$–the book-to-market ratio-based decile of the firm from the most recent calendar year.

The dummy variable coefficients capture the mean returns to various categories of stocks based on momentum and fundamentals. The interaction terms in equation (1) capture the dependence of momentum effects within winners and losers based on fundamentals. The table reports time series means of coefficients with associated Fama-Macbeth t-statistics using data from 1973 to 2015. Models 1–3 provide results for tests using 6-month buy-and-hold returns for the stock price momentum and fundamentals-based categories with controls for NYSE size-based decile ranks, b/m deciles and extreme momentum. Model 4 presents results for 12-month buy-and-hold returns during the first year after portfolio formation. Models 5 and 6 provide results for the subsequent 2 years.

The table presents two tests based on the estimated coefficients to analyse the interaction between momentum and fundamentals. The first coefficient test reports a test of the differences in returns of firms in Winners and Losers categories, that is Winners–Losers. With interaction terms included in the regression (models 2–6), this test can be interpreted as Winners and Losers with *inconsistent* fundamentals (i.e. after separating out winners and losers with mid and consistent fundamentals). In models 2–6, the first coefficient test is:

$$\begin{aligned}\text{Inconsistent Mom.} \times \text{Fund.} &= \text{Winners} - \text{Losers}\\ &= (\text{Winners} + \text{Weak Winners})\\ &\quad - (\text{Losers} + \text{Strong Losers})\end{aligned} \tag{2}$$

Models 3 and 4 reveal that this portfolio yields a reversal of −4.35 percent (*t*-statistic −3.13) and −7.79 percent (*t*-statistic −3.13) for the 6- and 12-month buy-and-hold periods, respectively, indicating that if we take away mid and full consistency-based momentum stocks, there is reversal in the momentum portfolio. Coefficient test 2 reports a test of the difference in average returns of firms based on consistency between stock price momentum and fundamentals defined as:

$$\begin{aligned}\text{Con. Mom. and Fund.} = {} & [\text{Winners} + \text{Winners} \times \text{Strong}] - [\text{Losers}\\ & + \text{Losers} \times \text{Weak}]\end{aligned} \tag{3}$$

Models 3 and 4 (with all controls) show that this tests yields a 6.96 percent (*t*-statistic 4.87) and 10.17 percent (*t*-statistic 5.08) difference in winner and loser portfolios for the 6- and 12-month buy-and-hold periods, respectively, indicating that there is significant and prolonged momentum over the following year when stock price performance has been consistent with fundamentals. This supports the central thesis of this paper that momentum stocks continue to exhibit momentum when there is consistency with fundamentals and reversals otherwise.

To address the possibility that sorting on fundamentals simply produces more extreme momentum-based stock, note that we introduce dummy variables for momentum deciles 1 and 10 in models 3–6. This should absorb any potential effect of more extreme momentum stocks if present. Given that our results are not affected by these controls, our results are not a consequence of choosing more extreme momentum stocks to achieve enhanced returns.

In models 5 and 6, we examine the behaviour of momentum stocks during an additional 2 years in the future. In model 5 (year *t*+2), the inconsistent momentum and fundamentals coefficient test yields an additional −4.71 percent (*t*-statistic −2.27) reversal while there is no further continuation of momentum based on the consistent momentum- and fundamentals-based test. In year 3, there are no further reversals or momentum in any category.

To summarise, the empirical tests in Table 3 demonstrate that the behaviour of momentum stocks depends on the degree to which expectations reflected in past stock returns are consistent with a firm's fundamentals as we hypothesise in our central hypothesis.

4.3. Fama-Macbeth cross-sectional regressions controlling for Piotroski and So (2012) interactions

Piotroski and So (2012) (PS) demonstrate that the value/glamour effect and *F*-score-based fundamentals interact. PS find that the value-glamour effect exists when fundamentals are more inconsistent with the value and glamour characteristics of stocks. In order to ensure that our findings do not overlap with theirs, we directly control for interactions between the value/glamour anomaly and fundamentals as constructed in their paper. Table 4 presents time series means of coefficients from annual Fama-Macbeth type regressions while controlling for PS interactions between the book-to-market ratio and fundamentals for the sample period 1973–2015. Similar to PS, the dependent variable in each regression is firm level future 12-month buy-and-hold stock return, measured starting 4 months after fiscal year-end for the first (models 1–4), second (model 5) and third (model 6) years in the future. Independent variables include dummy variables assigned as described below based on momentum, b/m and fundamentals-based categories. We estimate the following regression annually using all firms with data available on their momentum, b/m and fundamentals-based characteristics:

$$\begin{aligned} R_{t+1,i} = {} & a_{0,t} + a_{1,t} * Glamour_{t,i} + a_{2,t} * Glamour_{t,i} \times MidF_{t,i} \\ & + a_{3,t} * Glamour_{t,i} \times Weak_{t,i} + a_{4,t} * Value_{t,i} + a_{5,t} * Value_{t,i} \\ & \times MidF_{t,i} + a_{6,t} * Value_{t,i} \times Strong_{t,i} + b_{0,t} + b_{1,t} * Winners_{t,i} \\ & + b_{2,t} * Winners \times MidFscore_{t,i} + b_{3,t} * Winners \times Strong_{t,i} \\ & + b_{4,t} * Losers_{t,i} + b_{5,t} * Losers \times MidFscore_{t,i} + b_{6,t} * Losers \\ & \times Weak_{t,i} + c_{1,t} * Sizerank_{t,i} + c_{2,t} * SUErank_{t,i} + e_{t,i} \end{aligned}, \tag{4}$$

where $Glamour_{t,i}$–dummy variable = 1 if the firm falls into b/m deciles (1–3) and 0 otherwise, $Value_{t,i}$–dummy variable = 1 if the firm falls into b/m deciles (8–10) and 0 otherwise.

These definitions of Value and Glamour are as in Piotroski and So (2012). The remaining variables are described in the Appendix.

Table 4 reports time series means of coefficients with associated Fama-Macbeth *t*-statistics. Coefficient test 1 in model 1 confirms the basic value/glamour effect. Coefficient test 1 in models 2–4 reports a test of the difference in annual returns of firms based on congruence between fundamentals and b/m, defined as:

$$\text{Con. Fund. and B/M} = [\text{Value}] - [\text{Glamour}] \tag{5}$$

Table 4
Fama-Macbeth regressions of future 1-year buy & hold stock returns controlling for piotroski & so effects

	Year t+1				Year t+2	Year t+3
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	16.50%	15.39%	15.85%	17.08%	19.01%	18.89%
	5.41	*4.91*	*6.48*	*6.11*	*6.44*	*6.49*
Glamour	−2.91%	0.06%	−1.38%	−0.97%	−1.60%	−1.06%
	−1.86	*0.05*	*−1.13*	*−0.78*	*−1.11*	*−0.84*
Glamour × Mid-F		−3.35%	−1.79%	−1.71%	−1.54%	−0.92%
		−3.68	*−2.28*	*−2.14*	*−1.64*	*−1.17*
Glamour × Weak		−8.36%	−4.39%	−4.52%	−0.74%	−0.72%
		−4.24	*−2.56*	*−2.69*	*−0.33*	*−0.29*
Value	2.50%	−3.05%	−0.39%	−0.57%	−1.28%	2.01%
	2.74	*−2.41*	*−0.26*	*−0.40*	*−0.69*	*0.78*
Value × Mid-F		5.09%	3.15%	2.75%	2.39%	−0.93%
		3.28	*1.88*	*1.62*	*1.35*	*−0.45*
Value × Strong		9.00%	5.66%	5.27%	5.17%	0.91%
		4.97	*3.21*	*2.95*	*2.98*	*0.48*
Winners			−1.94%	−2.20%	−1.42%	−0.32%
			−0.88	*−1.02*	*−0.60*	*−0.15*
Winners × Mid-*F*-score			2.90%	2.92%	0.68%	1.39%
			1.80	*1.85*	*0.30*	*0.73*
Winners × Strong			5.36%	5.28%	2.22%	1.06%
			2.40	*2.39*	*0.92*	*0.53*
Losers			−0.60%	−0.29%	2.13%	−0.39%
			−0.52	*−0.25*	*1.84*	*−0.43*
Losers × Mid-*F*-score			−2.07%	−2.10%	0.11%	0.95%
			−2.46	*−2.50*	*0.11*	*0.87*
Losers × Weak			−5.74%	−5.88%	−1.91%	1.92%
			−3.86	*−4.01*	*−1.15*	*0.81*
Decile (Mktval)	−0.19%			−0.26%	−0.37%	−0.39%
	−0.85			*−1.22*	*−1.64*	*−1.86*
Avg. # of Firms	2,210	2,205	2,201	2,200	2,082	1,963
Avg. Adj. R^2	2.29%	3.20%	3.30%	4.05%	3.24%	3.10%
Coefficient tests						
1. Value - Glamour	5.40%	−3.11%	0.99%	0.40%	0.33%	3.07%
	2.50	*−1.62*	*0.48*	*0.21*	*0.14*	*1.11*
2. Piotroski-So B/M Strategy		14.25%	11.04%	10.19%	6.23%	4.69%
		4.46	*4.24*	*3.87*	*2.01*	*1.27*
3. Winners - Losers			−1.34%	−1.91%	−3.55%	0.07%
			−0.53	*−0.77*	*−1.79*	*0.03*
4. Consistent Momentum & Fundamentals			9.75%	9.25%	0.59%	−0.78%
			4.26	*4.19*	*0.27*	*−0.29*

T-statistics in italics. This table presents time series means of coefficients from Fama-Macbeth type regressions while controlling for Piotroski and So (2012) interactions between book-to-market ratio and fundamentals for the sample period 1973–2015. The dependent variable in each regression is firm level future buy-and-hold 6- or 12-month stock return. The 12-month stock return is measured starting 4 months after fiscal year-end for up to 3 years in the future. In models 1–4, the dependent variable is the 12-month return for months 4–15. In models 5 and 6, the dependent variable is the 12-month return for months 16 to 27, and 28–39 after fiscal year-end. Independent variables include dummy variables as described in the Appendix based on momentum-based and fundamentals-based categories as described in notes to panel A of Table 2. The momentum tercile of each firm is identified as of 3 months after fiscal year-end. Fundamentals measures are described in notes to Table 2. Following Piotroski and So (2012), we also assign book-to-market based deciles using the fiscal year-end book-to-market ratio of the firm calculated as book value of common equity (Compustat variable CEQ) divided by market value of equity (Compustat PRCC_f * CSHO). Firms with stock prices below $5/share as of momentum formation are excluded.

The following cross-sectional regression is estimated for each period using all firms with data available on their momentum and fundamentals-based categories:

$$\begin{aligned} R_{t+1,i} = {} & a_{0,t} + a_{1,t} * Glamour_{t,i} + a_{2,t} * Glamour_{t,i} \times MidF_{t,i} + a_{3,t} * Glamour_{t,i} \times Weak_{t,i} \\ & + a_{4,t} * Value_{t,i} + a_{5,t} * Value_{t,i} \times MidF_{t,i} + a_{6,t} * Value_{t,i} \times Strong_{t,i} + b_{0,t} \\ & + b_{1,t} * Winners_{t,i} + b_{2,t} * Winners \times MidFscore_{t,i} + b_{3,t} * Winners \times Strong_{t,i} \\ & + b_{4,t} * Losers_{t,i} + b_{5,t} * Losers \times MidFscore_{t,i} + b_{6,t} * Losers \times Weak_{t,i} \\ & + c_{1,t} * Sizerank_{t,i} + c_{2,t} * SUErank_{t,i} + e_{t,i} \end{aligned}$$

All variables are described in the Appendix.

The table also reports time series means of coefficients with associated Fama-Macbeth *t*-statistics.

Coefficient test (1) reports a test of the difference in average returns of firms in Glamour and Value categories. Coefficient test (2) reports the difference in returns based on the Piotroski and So (2012) 'Incongruent' strategy defined as:

[Value + Value × Strong] – [Glamour + Glamour × Weak]

Coefficient test (3) reports a test of the difference in returns of firms based on inconsistency between stock price momentum and fundamentals (*F*-score), defined as:

[Winners + Winners × Weak] – [Losers + Losers × Strong]

Coefficient test (4) reports a test of the difference in returns of firms based on consistency between stock price momentum and fundamentals (*F*-score), defined as:

[Winners + Winners × Strong] – [Losers + Losers × Weak]

This test duplicates the PS effect in model 2, indicating that the b/m effect is not present when b/m and fundamentals are congruent. Coefficient test 2 in models 2–4 reports a test of the differences in returns of firms based on congruence between fundamentals and b/m, defined as:

$$\text{Incon. Fund. and B/M} = [\text{Value} + \text{Value} \times \text{Strong}] - [\text{Glamour} + \text{Glamour} \times \text{Weak}] \tag{6}$$

Model 2 confirms that this test yields the PS effect that there are significant average returns to a strategy based on incongruent fundamentals and b/m (14.25 percent, t-statistic 4.46). Coefficient tests 1 and 2 in model 2 confirm the PS effect.

In models 3–4, we introduce interaction variables based on fundamentals and momentum. Coefficient test 3 reports a test of the differences in annual returns of firms based on inconsistency between stock price momentum and fundamentals (F-score), defined as:

$$\text{Incon. Mom. and Fund.} = [\text{Winners}] - [\text{Losers}] \tag{7}$$

The results indicate that while there is still some reversal during the first year when momentum and fundamentals are inconsistent, this effect is statistically insignificant (t-statistic = -0.77). However, coefficient test 4 reports a test of the difference in annual returns of firms based on consistency between stock price momentum and fundamentals (F-score), defined as:

$$\text{Con. Mom. and Fund.} = [\text{Winners} + \text{Winners} \times \text{Strong}] - [\text{Losers} + \text{Losers} \times \text{Weak}] \tag{8}$$

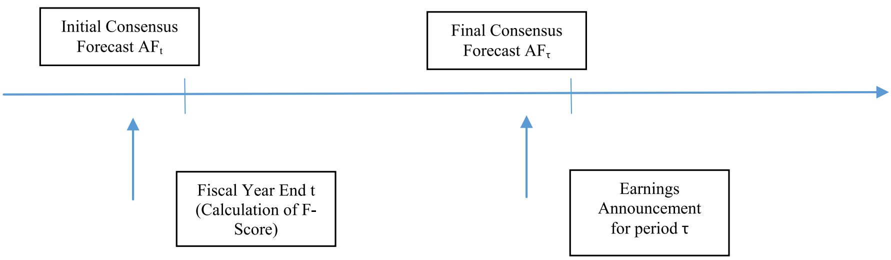
In models 3 and 4, this difference is 9.75 and 9.25 percent with t-statistics of 4.26 and 4.19, respectively, affirming the results documented in Tables 2 and 3. The tests reported in Table 4 confirm that interaction between b/m and fundamentals does not explain interaction between momentum and fundamentals.

4.4. *Earnings announcement returns and analysts' revisions*

Thus far, we have examined buy-and-hold stock returns to categories based on momentum and fundamentals derived from financial statement analysis. While stock returns reflect potential changes in expectations, cross-sectional variation in longer period returns can also reflect differences in risks. In order to provide further evidence on whether the effects documented in this study reflect potential errors in the market's expectations, we examine analysts' forecast revisions and earnings announcement returns. The advantage of using analysts' forecast revisions is that it provides a non-price-based measure of changes in expectations because analyst forecasts are used by investors. On the other hand, analysts are not proxies for investors because they do not set stock market prices through their trading. Nonetheless, if analysts suffer the same biases as investors, then changes in their expectations should provide compelling evidence that the effects documented using stock returns support our central hypothesis. Similarly, an examination of earnings announcement returns is useful because differences in short window returns across stocks are unlikely to be due to differences in risk (La Porta *et al.*, 1997).

4.4.1. Analysts' revisions

In order to track changes in analysts' expectations, we perform tests similar to the regression-based tests in Table 3 but replace the buy-and-hold stock return of a firm with a measure of revision in analysts' consensus earnings forecasts. In order to calculate the analyst revision, we collect the initial consensus earnings per share forecast from IBES summary files as the last consensus forecast available prior to the fiscal year-end before portfolio formation. For the forecast period under examination, we then collect the final consensus forecast available prior to the earnings announcement for the forecasted fiscal period. The periods for which we examine revisions in forecasts pertain to the next four quarterly earnings announcements and the earnings announcement for the following fiscal year. The diagram below illustrates the calculation of the forecast revision:



For each firm *i*, we calculate the forecast revision as the difference between the final and initial forecast scaled by the share price as of the initial forecast (following Clement *et al*., 2011)[5] :

$$Rev_{\tau-t,i} = [\mathrm{AF}_t - \mathrm{AF}_\tau]/\mathrm{Price}_t \tag{9}$$

Using analyst forecast revisions as the dependent variable, we estimate the following dummy variable regression:

$$\begin{aligned} Rev_{\tau-t,i} = {} & a_{0,t} + a_{1,t} * Winners_{t,i} + a_{2,t} * Winners \times MidFscore_{t,i} \\ & + a_{3,t} * Winners \times Strong_{t,i} + a_{4,t} * MedMom \times Strong_{t,i} \\ & + a_{5,t} * MedMom \times Weak_{t,i} + a_{6,t} * Losers_{t,i} + a_{7,t} * Losers \\ & \times MidFscore_{t,i} + a_{8,t} * Losers \times Weak_{t,i} \\ & + c_{1,t} * Sizerank_{t,i} + c_{2,t} * BMrank_{t,i} + e_{t,i} \end{aligned} \tag{10}$$

[5] Our results are essentially the same if we scale by balance sheet asset value per share instead of price per share.

Table 5
Fama-Macbeth regressions of future quarterly and annual analyst revisions for price momentum and fundamentals- based categories

	Qtr t+1		Qtr t+2		Qtr t+3		Qtr t+4		Year t+1	
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Intercept	−0.03%	−0.01%	−0.02%	−0.01%	0.01%	0.01%	0.01%	0.01%	0.01%	0.05%
	−2.51	*−1.33*	*−1.69*	*−1.46*	*0.78*	*0.89*	*0.76*	*1.39*	*0.05*	*0.49*
Winners	0.04%	−0.08%	0.03%	−0.02%	0.03%	−0.01%	0.03%	0.00%	0.36%	−1.30%
	6.54	*−4.80*	*6.97*	*−1.00*	*4.94*	*−0.64*	*6.80*	*−0.39*	*3.18*	*−5.94*
Winners × Mid-*F*-score		0.12%		0.06%		0.04%		0.03%		1.60%
		7.52		*2.42*		*2.09*		*2.45*		*7.54*
Winners × Strong		0.17%		0.09%		0.07%		0.06%		2.73%
		8.50		*4.05*		*3.30*		*4.77*		*12.41*
Med Mom × Strong		0.06%		0.03%		0.02%		0.00%		0.94%
		8.18		*4.38*		*4.12*		*0.74*		*9.89*
Med Mom × Weak		−0.12%		−0.04%		−0.03%		−0.03%		−1.44%
		−4.92		*−4.69*		*−3.07*		*−2.48*		*−8.75*
Losers	−0.12%	−0.02%	−0.07%	−0.03%	−0.06%	−0.03%	−0.06%	−0.03%	−0.44%	0.86%
	−11.18	*−2.01*	*−9.27*	*−2.90*	*−7.73*	*−2.83*	*−6.73*	*−2.82*	*−4.73*	*6.48*
Losers × Mid-*F*-score		−0.08%		0.0%		−0.02%		−0.03%		−1.24%
		−7.64		*−4.16*		*−2.68*		*−2.33*		*−12.19*
Losers × Weak		−0.25%		−0.10%		−0.07%		−0.05%		−2.71%
		−8.96		*−7.29*		*−6.12*		*−3.79*		*−12.73*
Decile (Mktval)	0.01%	0.01%	0.003%	0.002%	0.001%	0.00%	0.001%	0.00%	0.04%	0.02%
	5.29	*3.67*	*2.70*	*1.86*	*0.77*	*0.12*	*0.95*	*0.31*	*2.47*	*1.87*
Decile (Btom)	−0.03%	−0.03%	−0.02%	−0.02%	−0.02%	−0.02%	−0.01%	−0.01%	−0.27%	−0.26%
	−10.21	*−10.67*	*−8.22*	*−8.27*	*−8.07*	*−8.20*	*−6.62*	*−6.76*	*−11.26*	*−13.62*
Avg. # of Firms	1,705	1,699	1,434	1,428	1,399	1,393	1,322	1,316	1,634	1,628
Avg. Adj. R^2	5.51%	7.58%	4.22%	5.41%	3.75%	4.75%	3.13%	4.07%	10.07%	20.56%

(continued)

Table 5 (continued)

Variable	Qtr t+1 Model 1	Qtr t+1 Model 2	Qtr t+2 Model 3	Qtr t+2 Model 4	Qtr t+3 Model 5	Qtr t+3 Model 6	Qtr t+4 Model 7	Qtr t+4 Model 8	Year t+1 Model 9	Year t+1 Model 10
Coefficient Tests										
1. Winners - Losers	0.16%	−0.06%	0.11%	0.01%	0.09%	0.02%	0.09%	0.03%	0.80%	−2.16%
	11.72	*−2.63*	*10.08*	*0.40*	*8.02*	*0.76*	*8.35*	*1.64*	*6.56*	*−7.19*
2. Consistent Momentum & Fundamentals		0.36%		0.20%		0.16%		0.14%		3.28%
		10.74		*12.10*		*10.80*		*7.57*		*20.72*
3. Consistent - Inconsistent		0.42%		0.19%		0.14%		0.11%		5.44%
		9.58		*6.10*		*5.76*		*6.40*		*13.40*

T-statistics in italics. This table presents time series means of coefficients from Fama-Macbeth type regressions for the sample 1973–2015. The dependent variable in each regression is the analysts' earnings estimate revision calculated as:

$$Rev_{\tau-t,i} = [\text{Last Estimate}_{\text{BeforeAnn}} - \text{Last Estimate}_{\text{BeforeFiscalYearend}}]/\text{Last Price}_{\text{BeforeFiscalYearend}}$$

The revision for period τ is calculated as the last mean consensus estimate of period τ earnings prior to the earnings announcement minus the last consensus estimate for period τ prior to the fiscal year-end at which the *F*-score is calculated, scaled by the stock price as of the fiscal year-end. In models 1–8, we examine analyst estimates for 5 fiscal periods: the fiscal quarter related to the first, second, third and fourth quarterly announcement after fiscal year-end. We also examine the analyst revision of next year's annual earnings in models 9 and 10. Firms with stock prices below $5/share as of momentum formation are excluded.

Independent variables include dummy variables assigned as described in the Appendix based on momentum-based and fundamentals-based categories as described in notes to panel A of Table 2. The momentum tercile of each firm is identified as of 3 months after fiscal year-end. Fundamentals measures are described in notes to Table 2. We also control for returns to extreme winners and losers defined as portfolios of firms based on deciles 1 and 10 based on past stock price momentum.

The following cross-sectional regression is estimated each period using all firms with data available on their momentum- and fundamentals-based characteristics:

$$
\begin{aligned}
Rev_{\tau-t,i} = {} & a_{0,t} + a_{1,t} * Winners_{t,i} + a_{2,t} * Winners \times MidFscore_{t,i} + a_{3,t} * Winners \times Strong_{t,i} \\
& + a_{4,t} * MedMom \times Strong_{t,i} + a_{5,t} * MedMom \times Weak_{t,i} \\
& + a_{6,t} * Losers_{t,i} + a_{7,t} * Losers \times MidFscore_{t,i} + a_{8,t} * Losers \times Weak_{t,i} \\
& + c_{1,t} * Sizerank_{t,i} + c_{2,t} * BMrank_{t,i} + e_{t,i}
\end{aligned}
$$

All variables are described in the Appendix.
The table reports time series means of coefficients with associated Fama-Macbeth *t*-statistics. The table also reports the average number of firms used in the cross-sectional regressions. The first coefficient test reports a test of the differences in mean analyst revisions of momentum-based portfolios based on Winners and Losers categories. The second test reports a test of the difference in mean analyst revisions of portfolios based on consistency between stock price momentum and fundamentals defined as:

$$[\text{Winners} + \text{Winners} \times \text{Strong}] - [\text{Losers} + \text{Losers} \times \text{Weak}]$$

All variables are as described in the Appendix. This regression is similar to equation (1) except that the dependent variable (stock return) is replaced by the analyst revision described above.

We report estimates from equation (10) above in Table 5. The table reports time series means of coefficients with associated Fama-Macbeth *t*-statistics. The first coefficient test in Table 5 reports a test of the difference in mean analyst revisions of momentum-based portfolios based on Winners and Losers categories without incorporating the effects of fundamentals. The second test reports a test of the difference in mean analyst revisions of portfolios based on consistency between stock price momentum and fundamentals defined as:

$$[\text{Winners} + \text{Winners} \times \text{Strong}] - [\text{Losers} + \text{Losers} \times \text{Weak}]$$

Models 1–8 report tests based on revisions in analysts' estimates for the next four quarterly earnings while controlling for the size and book-to-market decile of the firm. In model 1 for the pure momentum strategy, we find that the first quarterly earnings revision is 0.16 percent (*t*-statistic 11.72). However, once we add controls for consistency with fundamentals, the analysts' forecast revision reflects a reversal in expectations when fundamentals are inconsistent with past stock returns (coefficient test 1 in model 2); the average forecast revision is −0.06 percent (*t*-statistic −2.63). By contrast, when past returns and fundamentals are consistent, analysts significantly revise their estimates in a manner consistent with the results in Table 3 derived using stock returns. The mean forecast revision for the consistent portfolio is 0.36 percent (*t*-statistic 10.74) in model 2, coefficient test 2. The difference in the consistent and inconsistent portfolio is a significant 0.42 percent (*t*-statistic 9.58).

Differences in revisions of consistent vs. inconsistent portfolios are similar for the following three quarters. The effect is much larger in magnitude when we examine revision in the forecasts for next annual earnings in model 10. For the inconsistent portfolio, we observe a reversal of −2.16 percent (*t*-statistic −7.19), and for the consistent portfolio, we observe an upward revision of 3.28 percent (*t*-statistic 20.72) for a difference of 5.44 percent (*t*-statistic 13.40). These results reflect a pattern of expectations very similar to that observed using stock returns in Table 3.

4.4.2. Earnings announcement returns

In Table 6, we examine earnings announcement returns. Table 6 is similar to the portfolio level tests in Table 2 except that instead of the annual size-adjusted returns, we collect market-adjusted +/−2 days earnings announcement window returns during the 12 months following formation of momentum- and fundamentals-based categories (i.e. starting 4 months after fiscal year-end). Table 6 reports earnings announcement window returns for categories formed on stock price momentum and fundamentals. The measurement of momentum and fundamentals is as described in notes to Table 2. The earnings announcement window return is defined as buy-and-hold returns for +/−2 days around the earnings report date minus the buy-and-hold value-weighted market return around the same days. For each firm, we aggregate the announcement window returns for earnings announcements that occur during 12 months after portfolio assignment (starting 4 months after fiscal year-end). Each calendar year, we take the cross-sectional average of this return across firms in each portfolio. We then calculate the time series average for each portfolio which is reported in the table along with the associated *t*-statistic.

Table 6 shows the difference in returns to momentum stocks that are either inconsistent with fundamentals or consistent with fundamentals. These tests yield a similar conclusion to that drawn in Table 2 since consistency produces earnings announcement returns of 2.26 percent (*t*-statistic 4.09), though the economic magnitude is much smaller than the full year buy-and-hold return results documented in previous tables. The results of Table 6 are consistent with the substance of the findings in previous tables.

4.5. Characteristics of an investment strategy based on congruence between stock price momentum and fundamentals

In the previous sections, we examined the dependence of momentum behaviour on fundamentals using event time analysis; that is relative to the fiscal year-end. Fiscal year-end months vary for firms between January and December. To simulate the implementation of a trading strategy, we switch to portfolio formation in calendar time. Prior studies such as Jegadeesh and Titman (2001) hold momentum stocks for up to 6 months before turning them over.[6] In keeping with this, we form momentum portfolios twice a year, once in January and once in June using the past 6-month stock return (skipping current month). We drop firms with share prices below $5/share. We buy and hold the June portfolio for the next 6 months (July–Dec) and the January portfolio for the next 5 months (February–June). We do not invest in January because prior studies show that the momentum effect is negative in January. This provides 83 *non-overlapping* 6-month holding periods for analysis. After establishing momentum ranks, to each firm we attach its most recent *F*-score (with a minimum gap of 3 months to ensure financial statement availability). Then, we create an equally weighted portfolio long in Strong Winners and short in Weak Losers (Consistent Mom/Fund henceforth). In summary, portfolios are formed in January, held from February to June and liquidated before forming new portfolios which are held from July to December and then liquidated. The

[6] Jegadeesh and Titman (2001) create equally weighted overlapping portfolios where 1/6th of the portfolio is liquidated each month. We avoid this technique because this entails frequent rebalancing to establish equally weighted portfolios.

Table 6
Mean earnings announcement returns to portfolios based on stock price momentum and fundamentals

		Winners	Med Mom	Losers	Winners - Losers	No. of periods
	Mean Ret	1.55%	1.39%	0.87%	0.68%	42
	T-stat	6.31	6.73	2.95	2.42	
	Avg Firms/Year	765	664	772		
Strong F (7–9)	1.69%	2.18%	1.54%	0.97%	1.20%	42
T-stat	7.90	7.56	6.17	2.83	4.38	
Avg Firms/Year	562	227	181	154		
Mid-F (4–6)	1.27%	1.47%	1.38%	1.02%	0.45%	42
T-stat	5.28	5.67	5.53	3.10	2.22	
Avg Firms/Year	1362	454	419	489		
Weak F (0–3)	0.15%	0.15%	0.31%	−0.08%	0.23%	42
T-stat	0.39	0.29	0.54	−0.16	2.00	
Avg Firms/Year	277	84	65	128		
Strong - Weak	1.54%	2.02%	1.23%	1.05%		
T-stat	*4.17*	*4.38*	*1.62*	*0.37*		
	Tests					
	Inconsistent Momentum and Fundamentals					
	Winners × Weak - Losers × Strong		−0.82%			
	T-statistic		−1.41			
	Consistent Momentum and Fundamentals					
	Winners × Strong - Losers × Weak		2.26%			
	T-statistic		4.09			

This table reports earnings announcement window returns for portfolios formed on stock price momentum and fundamentals. The measurement of momentum and fundamentals is as described in notes to panel A of Table 2. Earnings announcement window is defined as buy-and-hold returns for +/−2 days around the earnings report date minus the buy-and-hold value-weighted market return around the same days. For each firm, we aggregate the announcement window returns for earnings announcements that occur during 12 months after portfolio assignment (starting 4 months after fiscal year-end). Each calendar year, we take the cross-sectional average of this return across firms in each portfolio. We then calculate the time series average for each portfolio which is reported in the table along with the associated *t*-statistic.

momentum characteristic is updated twice a year at portfolio formation while *F*-scores are updated once a year.

To estimate abnormal returns to these portfolios, we obtain the monthly returns to each component portfolio used to form three Fama-French factors, Mktrf, SMB and HML (Fama and French, 1993). These include the market portfolio, a risk-free asset, two-sized-based portfolios, and three b/m-based portfolios. We cumulate the monthly returns of these portfolios and calculate the Mktrf, SMB and HML factor returns for each July–December and February–June holding period. We use these in the following time series regression to calculate the Fama-French 3-factor abnormal return (FF-α) for the long-short momentum and fundamentals-based portfolio using the 83 half-year holding periods:

$$R_{Win\times Str-Los\times Wk,t} = \alpha_{FF} + \beta_{mkt}R_{mktrf} + \beta_{smb}R_{smb} + \beta_{hml} + e_t \tag{11}$$

We also run a regression with the long-short portfolio based only on a pure momentum strategy over the same holding periods.

Using the 83 half-year holding-period returns, Table 7 reports the essential characteristics of both the pure momentum strategy as well as the Consistent Mom/Fund strategy. These include raw average returns, standard deviations, the FF-α, the ex-post Sharpe ratio of the long-short portfolio and the average number of firms in the portfolio. In panel A of Table 7, we report these characteristics for the full 1973–2015 sample using either momentum terciles, quintiles and deciles, that is three, five and 10 momentum-based ranks. For three momentum ranks, the FF-α of the Consistent Mom/Fund strategy is 7.06 percent/6-month period (t-statistic 7.16) on average compared to 3.31 percent (t-statistic 4.32) for the pure momentum strategy. These 6-month holding-period returns are larger than those reported in earlier tables due to the exclusion of the January returns when prior studies show the momentum effect turns negative. The t-statistics for the Consistent Mom/Fund strategy are large because for the vast majority of the periods the strategy generates significant positive returns. In this sense, the standard deviation of 8.59 percent for this portfolio is misleading because most of this volatility is on the upside.

We calculate the Sharpe ratio of the Consistent Mom/Fund strategy to be 0.78 compared to 0.50 for the pure momentum strategy over the same period. This indicates that on a risk-adjusted basis, the Consistent Mom/Fund strategy is superior to the pure momentum strategy while requiring positions in fewer than 1/3rd of the number of firms as in the pure momentum strategy. Very similar results are also notable in panel A using momentum quintiles and deciles. It is also useful to note that the Sharpe ratio of the terciles-based Consistent Mom/Fund strategy in panel A is superior to the deciles-based pure momentum strategy; that is, the former produces a similar return with a lower standard deviation while trading in fewer stocks.

Recent studies suggest that the momentum effect has weakened since the turn of the century. In panel B of Table 7, we report the characteristics of our calendar time investment strategies for the 2000–2015 sample period. Notably, the terciles-based pure momentum strategy generates a 3-factor alpha of only 1.92 percent with a t-statistic of 1.52. By contrast, the consistent momentum $\times$ fundamentals

Table 7
Characteristics of a 6-month holding-period investment strategy

	Std. Momentum Strategy			Consistent Mom/Fund		
	Winners	Losers	W-L	Winners	Losers	W-L
Panel A: Sample period 1973–2015						
3 Momentum groups						
Mean return	7.72%	4.52%	3.20%	8.68%	2.01%	6.67%
SD	13.98%	13.43%	6.38%	13.72%	16.06%	8.59%
Sharpe ratio			0.50			0.78
FF-α			3.31%			7.06%
T-statistic FF-α			4.32			7.16
Turnover/Year	2×	2×	2×	2×	2×	2×
No. of holding periods	83	83	83	83	83	83
Average No. of firms	820	849		232	110	
5 Momentum groups						
Mean return	8.19%	3.60%	4.59%	9.14%	1.10%	8.04%
SD	15.3%	14.4%	8.35%	15.1%	17.2%	9.65%
Sharpe ratio			0.55			0.83
FF-α			4.86%			8.48%
T-statistic FF-α			4.91			7.52
Turnover/Year	2×	2×	2×	2×	2×	2×
No. of holding periods	83	83	83	83	83	83
Average No. of firms	514	525		142	76	
10 Momentum groups						
Mean return	9.01%	1.97%	7.03%	10.10%	-0.88%	10.98%
SD	17.38%	15.43%	10.83%	17.62%	19.08%	12.36%
Sharpe ratio			0.65			0.89
FF-α			7.34%			11.87%
T-statistic FF-α			5.81			8.03
Turnover/Year	2×	2×	2×	2×	2×	2×
No. of holding periods	83	83	83	83	83	83
Average No. of firms	260	264		70	43	
Panel B: Sample period 2000–2015						
3 Momentum groups						
Mean return	6.14%	4.46%	1.68%	7.48%	2.43%	5.05%
SD	14.19%	15.01%	6.26%	13.92%	17.67%	8.88%
Sharpe ratio			0.27			0.57
FF-α			1.92%			6.48%
T-statistic FF-α			1.52			4.21
Turnover/Year	2×	2×	2×	2×	2×	2×
No. of holding periods	29	29	29	29	29	29
Average No. of firms	848	940		214	128	

(continued)

Table 7 (continued)

	Std. Momentum Strategy			Consistent Mom/Fund		
	Winners	Losers	W-L	Winners	Losers	W-L
5 Momentum groups						
Mean return	6.16%	3.97%	2.19%	7.83%	2.11%	5.72%
SD	15.0%	16.2%	8.26%	15.2%	18.8%	10.03%
Sharpe ratio			0.26			0.57
FF-α			2.57%			7.16%
T-statistic FF-α			1.55			4.05
Turnover/Year	2×	2×	2×	2×	2×	2×
No. of holding periods	29	29	29	29	29	29
Average No. of firms	561	616		140	92	
10 Momentum groups						
Mean return	6.67%	3.12%	3.55%	8.66%	0.53%	8.12%
SD	16.27%	17.18%	9.74%	17.88%	20.62%	10.81%
Sharpe ratio			0.36			0.75
FF-α			3.88%			9.38%
T-statistic FF-α			1.95			4.63
Turnover/Year	2×	2×	2×	2×	2×	2×
No. of holding periods	29	29	29	29	29	29
Average No. of firms	297	323		70	55	

This table reports characteristics of an investment strategy based on stock price momentum and financial statement fundamentals using 6-month holding periods. We form momentum portfolios twice a year, once in January and once in June using the past 6-month stock return (skipping the current month). We drop firms with share prices below $5/share. We buy-and-hold the June portfolio for the next 6 months (July–December) and the January portfolio for the next 5 months (February–June). January returns are excluded. This provides 83 6-month holding periods for analysis. After establishing momentum ranks, to each firm we attach its most recent *F*-score with a lag of at least 3 months. Then, we create an equally weighted portfolio long in Strong Winners and short in Weak Losers (Consistent Mom/Fund). To estimate abnormal returns to these portfolios, we obtain the monthly returns to each portfolio used to form 3 Fama-French factors, Mktrf, SMB and HML. These portfolios include the market portfolio, a risk-free asset, 2 size-based portfolios and 3 b/m-based portfolios. We cumulate the monthly returns of these portfolios to form the Mktrf, SMB and HML factor returns for the July–December and February–June holding periods. We use these in the following time series regression to calculate the Fama-French 3-factor abnormal return (FF-α) for the long-short momentum and fundamentals-based portfolio using the 83 half-year holding periods:

$$R_{WinxStr-LosxWk,t} = \alpha_{FF} + \beta_{mkt} R_{mktrf} + \beta_{smb} R_{smb} + \beta_{hml} R_{hml} + e_t$$

We also run a regression with the long-short portfolio based only on a pure momentum strategy operating over the same holding periods. Using the 83 half-year holding-period returns, this table shows essential statistics of both the pure momentum strategy as well as the Consistent Mom/Fund strategy. These include raw average returns, standard deviation of

returns, the Fama-French alpha, the Sharpe ratio of the long-short portfolio and the average number of firms in the portfolio. We report these results based on momentum terciles, quintiles and deciles.
Panel A reports characteristics of the investment strategy for the full sample period of 1973–2015. Panel B reports characteristics for the 2000–2015 period.

strategy produces an abnormal return of 6.48 percent with a t-statistic of 4.21. These results suggest that the application of FSA to momentum strategies continues to generate significant abnormal returns in recent periods. Figure 1 shows a time series of 6-month holding-period returns to the enhanced strategy *vis-à-vis* a pure momentum-based strategy in calendar time.

We also perform (untabulated) tests similar to those in Tables 7A and B using a 5-factor model developed by Fama and French (2016). The 5-factor model adds factors based on operating profitability and asset growth to the regression in equation (10).[7] As expected, the inclusion of the profitability and investment factors reduces the performance of the momentum × fundamentals-based strategy in Table 7A by between 1/4th and 1/3rd, depending upon whether we use momentum quintiles or terciles (deciles-based results remain unaffected). This is because the F-score includes both profitability and investment-based variables so controlling for these factors should diminish the abnormal returns. Nonetheless, the abnormal returns to the strategy remain significant with the FF-alpha dropping from 8.48 to 6.15 percent per 6-month period (dropping from 17 to 12 percent annualised) with a t-statistic of 5.66 for the momentum quintiles × fundamentals-based strategy. Because profitability and investment-based variables in the F-score have not demonstrably been proven to reflect risk factors, we retain our 3-factor model results in Table 7.

The discussion above illustrates how understanding the interaction between momentum and fundamentals can help enhance a price-based momentum strategy.

4.6. *Additional robustness and sensitivity checks*

We perform additional robustness checks not reported in tables. First, a possible explanation for our primary results in Table 3 is that sorting on F-score simply sorts on the degree to which the recent earnings surprise (SUE) is consistent with the recent stock price momentum. In other words, can the interaction between SUE and momentum explain the interaction between fundamentals and momentum? If so, this would reduce the need for fundamental analysis beyond earnings because one can simply rely on recent earnings instead. To examine this, we introduce dummy variables

[7] Data for these factors are obtained from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

based on the interaction between the most recent SUE and stock price momentum in equation (1). We find essentially similar results to those in Table 3 despite controlling for interaction between SUE and momentum, indicating that FSA is significantly more powerful than using earnings alone.

Our main results hold in additional robustness tests after (i) controlling for interactions between book-to-market and stock price momentum, (ii) using a measure of momentum based on the past 12-month return instead of 6-month return, (iii) using quintiles or deciles of momentum instead of terciles in all our tables, (iv) starting the future return calculation period with 5 or 6 months after fiscal year-end instead of 4 and (v) dropping microcaps (NYSE-based capitalisation deciles 1 and 2).

5. Conclusions

In this study, we provide evidence on the usefulness of FSA in enhancing the risk-adjusted performance of momentum investing strategies. The potential for FSA to enhance momentum strategies arises because past price changes can be driven by fundamentals or non-fundamentals such as noise. Stocks experiencing non-fundamental-driven price changes are likely to experience return reversals and thus dropping these stocks from a momentum-based strategy is likely to enhance returns. Moreover, FSA can help identify stocks that are likely to exhibit persistent performance. Thus, to the extent past prices do not fully reflect this information, FSA can further enhance returns to momentum strategies.

Consistent with our expectations, we find that incorporating FSA into momentum investing substantially improves the performance of momentum strategies. For example, the average 1-year buy-and-hold return of firms where past stock price performance is consistent with fundamentals (i.e. *Strong* Winners–*Weak* Losers) is 11.59 percent over the year after portfolio formation compared to 4.35 percent from a pure momentum strategy (Winners–Losers) over the same period. The effect is remarkably robust in that it generates positive returns 88 percent of the time (37 of 42 years) and outperforms a pure momentum strategy 83 percent of the time (35 of 42 years). Moreover, we find that the ex-post Sharpe ratio of a 6-month holding-period strategy based on consistency between past stock price performance and fundamentals is 50 percent greater than that of a pure momentum strategy. These findings are robust to dropping microcaps (bottom 2 NYSE-based capitalisation deciles) and controlling for more extreme momentum stocks.

Our study has implications for both investment professionals and academics. For investment professionals, our findings suggest that a combined fundamentals–momentum strategy is not only more profitable and less risky than a pure momentum strategy, but is also likely to be more implementable. This is an important finding because of concerns that a pure momentum strategy may be too costly to implement. For academics, we extend research on the usefulness of FSA and provide insights into the behaviour of momentum stocks. More specifically, our results are more consistent with a mispricing explanation rather than a risk-based explanation of momentum.

References

Abarbanell, J. S., and B. J. Bushee, 1997, Fundamental analysis, future earnings, and stock prices, *Journal of Accounting Research* 35(1), 1–24.

Abarbanell, J. S., and B. J. Bushee, 1998, Abnormal returns to a fundamental analysis strategy, *Accounting Review* 73(1), 19–45.

Asness, C. S., 1997, The interaction of value and momentum strategies, *Financial Analysts Journal* 53(2), 29–36.

Asness, C. S., T. J. Moskowitz, and L. H. Pedersen, 2013, Value and momentum everywhere, *The Journal of Finance* 68(3), 929–985.

Avramov, D., T. Chordia, G. Jostova, and A. Philipov, 2007, Momentum and credit rating, *The Journal of Finance* 62(5), 2503–2520.

Badrinath, S. G., and S. Wahal, 2002, Momentum trading by institutions, *The Journal of Finance* 57(6), 2449–2478.

Bandarchuk, P., and J. Hilscher, 2012, Sources of momentum profits: evidence on the irrelevance of characteristics, *Review of Finance* 17(2), 809–845.

Barber, B. M., T. Odean, and N. Zhu, 2008, Do retail trades move markets?, *The Review of Financial Studies* 22(1), 151–186.

Barber, B. M., T. Odean, and N. Zhu, 2009, Systematic noise, *Journal of Financial Markets* 12(4), 547–569.

Barberis, N., A. Shleifer, and R. Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49(3), 307–343.

Berk, J. B., R. C. Green, and V. Naik, 1999, Optimal investment, growth options, and security returns, *The Journal of Finance* 54(5), 1553–1607.

Bhattacharya, D., W. Li, and G. Sonaer, 2017, Has momentum lost its momentum?, *Review of Quantitative Finance and Accounting* 48(1), 191–218.

Black, Fischer., 1986, Noise, *The Journal of Finance* 41(3), 528–543.

Choi, N. Y., and R. W. Sias, 2012, Why does financial strength forecast stock returns? Evidence from subsequent demand by institutional investors, *Review of Financial Studies* 25(5), 1550–1587.

Chordia, T., and L. Shivakumar, 2002, Momentum, business cycle, and time-varying expected returns, *The Journal of Finance* 57(2), 985–1019.

Chordia, T., and L. Shivakumar, 2006, Earnings and price momentum, *Journal of Financial Economics* 80(3), 627–656.

Clement, M. B., J. Hales, and Y. Xue, 2011, Understanding analysts' use of stock returns and other analysts' revisions when forecasting earnings, *Journal of Accounting and Economics* 51(3), 279–299.

Conrad, J., and G. Kaul, 1998, An anatomy of trading strategies, *Review of Financial Studies* 11(3), 489–519.

Daniel, K., and S. Titman, 1999, Market efficiency in an irrational world, *Financial Analysts Journal* 55(6), 28–40.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam, 1998, Investor psychology and security market under-and overreactions, *The Journal of Finance* 53(6), 1839–1885.

DeLong, J. B., A. Shleifer, L. H. Summers, and R. J. Waldmann, 1990, Noise trader risk in financial markets, *Journal of Political Economy* 98(4), 703–738.

Fama, F. E., and K. R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33(1), 3–56.
Fama, E. F., and K. R. French, 2008, Dissecting anomalies, *The Journal of Finance* 63 (4), 1653–1678.
Fama, E. F., and K. R. French, 2016, Dissecting anomalies with a five-factor model, *The Review of Financial Studies* 29(1), 69–103.
Fama, E. F., and J. D. MacBeth, 1973, Risk, return, and equilibrium: empirical tests, *The Journal of Political Economy* 81(3), 607–636.
Graham, B., and D. L. Dodd, 1934, *Security Analysis: Principles and Technique* (McGraw-Hill, New York, NY).
Griffin, J. M., X. Ji, and J. S. Martin, 2003, Momentum investing and business cycle risk: evidence from pole to pole, *The Journal of Finance* 58(6), 2515–2547.
Grinblatt, M., S. Titman, and R. Wermers, 1995, Momentum investment strategies, portfolio performance, and herding: a study of mutual fund behavior, *The American Economic Review* 85(5), 1088–1105.
Grossman, S. J., and J. E. Stiglitz, 1980, On the impossibility of informationally efficient markets, *The American Economic Review* 70(3), 393–408.
Hong, H., and J. C. Stein, 1999, A unified theory of underreaction, momentum trading, and overreaction in asset markets, *The Journal of Finance* 54(6), 2143–2184.
Hou, K., W. Xiong, and L. Peng, 2009, A tale of two anomalies: the implications of investor attention for price and earnings momentum, Available at SSRN 976394.
Huang, D., H. Zhang, and G. Zhou, 2017, Twin momentum, Available at SSRN 2894068.
Jegadeesh, N., and S. Titman, 1993, Returns to buying winners and selling losers: implications for stock market efficiency, *The Journal of Finance* 48(1), 65–91.
Jegadeesh, N., and S. Titman, 2001, Profitability of momentum strategies: an evaluation of alternative explanations, *The Journal of Finance* 56(2), 699–720.
Jegadeesh, N., and S. Titman, 2011, Momentum, *Annual Review of Financial Economics* 3(1), 493–509.
Johnson, T. C., 2002, Rational momentum effects, *The Journal of Finance* 57(2), 585–608.
Korajczyk, R. A., and R. Sadka, 2004, Are momentum profits robust to trading costs?, *The Journal of Finance* 59(3), 1039–1082.
Kumar, A., and C. Lee, 2006, Retail investor sentiment and return comovements, *The Journal of Finance* 61(5), 2451–2486.
La Porta, R., J. Lakonishok, A. Shleifer, and R. Vishny, 1997, Good news for value stocks: further evidence on market efficiency, *Journal of Finance* 52(2), 859–874.
Lesmond, D. A., M. J. Schill, and C. Zhou, 2004, The illusory nature of momentum profits, *Journal of Financial Economics* 71(2), 349–380.
Lev, B., and S. R. Thiagarajan, 1993, Fundamental information analysis, *Journal of Accounting Research* 31(2), 190–215.
Liu, L. X., and L. Zhang, 2008, Momentum profits, factor pricing, and macroeconomic risk, *Review of Financial Studies* 21(6), 2417–2448.
Mendel, B., and A. Shleifer, 2012, Chasing noise, *Journal of Financial Economics* 104(2), 303–320.
Mohanram, P. S., 2005, Separating winners from losers among low book-to-market stocks using financial statement analysis, *Review of Accounting Studies* 10(2), 133–170.
Nofsinger, J. R., and R. W. Sias, 1999, Herding and feedback trading by institutional and individual investors, *The Journal of finance* 54(6), 2263–2295.
Novy-Marx, R., 2015, Fundamentally, momentum is fundamental momentum, Working paper (University of Rochester).

O'Hara, M., 2003, Presidential address: liquidity and price discovery, *The Journal of Finance* 58(4), 1335–1354.
Ou, J. A., and S. H. Penman, 1989a, Financial statement analysis and the prediction of stock returns, *Journal of Accounting and Economics* 11(4), 295–329.
Ou, J. A., and S. H. Penman, 1989b, Accounting measurement, price-earnings ratio, and the information content of security prices, *Journal of Accounting Research* 27(Suppl), 111–144.
Piotroski, J. D., 2000, Value investing: the use of historical financial statement information to separate winners from losers, *Journal of Accounting Research* 38 (Suppl), 1–41.
Piotroski, J. D., and E. C. So, 2012, Identifying expectation errors in value/glamour strategies: a fundamental analysis approach, *Review of Financial Studies* 25(9), 2841–2875.
Sadka, R., 2006, Momentum and post-earnings-announcement drift anomalies: the role of liquidity risk, *Journal of Financial Economics* 80(2), 309–349.
Sagi, J. S., and M. S. Seasholes, 2007, Firm-specific attributes and the cross-section of momentum, *Journal of Financial Economics* 84(2), 389–434.
Shleifer, A., 2000, *Inefficient Markets: An Introduction to Behavioural Finance* (Oxford University Press, Oxford).
Shleifer, A., and L. H. Summers, 1990, The noise trader approach to finance, *The Journal of Economic Perspectives* 4(2), 19–33.
Shleifer, A., and R. W. Vishny, 1997, The limits of arbitrage, *The Journal of Finance* 52 (1), 35–55.
Verardo, M., 2009, Heterogeneous beliefs and momentum profits, *Journal of Financial and Quantitative Analysis* 44(4), 795–822.
Zhang, X., 2006, Information uncertainty and stock returns, *The Journal of Finance* 61 (1), 105–137.

Appendix

Variable descriptions

A.1. Variable measurement for *F*-score calculation

Piotroski's *F*-score (2000) is the sum of nine indicator variables that are defined using financial statement data. The variables are chosen based on traditional interest by valuation analysts in evaluating the strength of a firm's financial fundamentals. Piotroski categorises the nine signals into three categories: Profitability, Leverage and Liquidity, and Operating Efficiency. Details regarding the logic underlying these variables can be found in Piotroski (2000). Below, we describe the measurement of the variables used to calculate the *F*-score. Compustat data names are provided in quotations within parentheses.

1 ROA is income before extraordinary items ('IB') divided by the beginning of the year total assets ('AT'). The indicator variable I_ROA equals 1 if ROA $>$ 0 and 0 otherwise.

2 CFO is measured as the cash flow from operations ('CFO', measured as funds from operations when 'CFO' not available) scaled by beginning of year total assets ('AT'). The indicator variable I_CFO equals 1 if CFO $>$ 0 and 0 otherwise.
3 ACCRUAL is the difference between income before extraordinary items ('IB') scaled by beginning of year total assets ('AT') and cash flow from operations as described above. The indicator variable I_ACC equals 1 if ACCRUAL $<$ 0 and 0 otherwise.
4 DROA is measured as the difference between current year's ROA and the previous year's ROA. The indicator variable I_DROA equals 1 if DROA $>$ 0 and 0 otherwise.
5 DLEVER is measured as the difference between the current year's debt-to-assets ratio and the previous year's debt-to-assets ratio. The debt-to-assets ratio is measured as long-term debt ('DLT') divided by total assets ('AT'). The indicator variable I_DLEV equals 1 if DLEVER $<$ 0 and 0 otherwise.
6 DLIQUID is the difference between current year's current ratio and the previous year's ratio. The current ratio is measured as current assets ('ACT') divided by current liabilities ('CLT'). The indicator variable I_DLIQ equals 1 if DLIQUID $>$ 0 and 0 otherwise.
7 ISSUANCE is measured as the amount of stock issued by a firm in a given year ('SSTK'). The indicator variable I_SSTK equals 1 if DLIQ $<=$ 0 and 0 otherwise.
8 DMARGIN is measured as the difference between the current year's gross margin ratio and the previous year's ratio. The gross margin ratio is measured as one minus the ratio of cost of goods sold ('COGS') and net sales ('SALE'). The indicator variable I_DM equals 1 if DMARGIN $>$ 0 and 0 otherwise.
9 DTURN is measured as the difference between the current year's asset turnover ratio and the previous year's turnover ratio. The asset turnover ratio is measured as net sales ('SALE') divided by total assets ('AT'). The indicator variable I_DTURN equals 1 if DTURN $>$ 0 and 0 otherwise.

The aggregated *F*-score is calculated as: *F*-score = I_ROA+I_CFO+I_ACC +I_DROA+I_DLEV+I_LIQ+I_SSTK+I_DM+I_DTURN

Regression Variables in Tables

$R_{t+1,i}$–future 1-year buy-and-hold stock return of firm i beginning 4 months after fiscal year-end,
$Winners_{t,i}$–dummy variable = 1 if the firm falls into momentum tercile 3 as of 3 months after fiscal year-end and 0 otherwise,
$MedMom_{t,i}$–dummy variable = 1 if the firm falls into momentum tercile 2 as of 3 months after fiscal year-end and 0 otherwise,
$Losers_{t,i}$–dummy variable = 1 if the firm falls into momentum tercile 1 as of 3 months after fiscal year-end and 0 otherwise,

$Strong_{t,i}$–dummy variable = 1 if the firm falls into a Strong fundamentals category (F-scores 7–9) and 0 otherwise,
$MidFscore_{t,i}$–dummy variable = 1 if the firm falls into a medium fundamentals category (F-scores 4–6) and 0 otherwise,
$Weak_{t,i}$–dummy variable = 1 if the firm falls into a Weak fundamentals category (F-scores 0–3) and 0 otherwise,
$ExtremeWinners_{t,i}$–dummy variable = 1 if the firm falls into decile 10 based on its past 6-month stock return and 0 otherwise,
$ExtremeLosers_{t,i}$–dummy variable = 1 if the firm falls into decile 1 based on its past 6-month stock return and 0 otherwise,
$Sizerank_{t,i}$–the NYSE-based size decile of the firm from the most recent calendar year,
$BMrank_{t,i}$–the book-to-market ratio-based decile of the firm from the most recent calendar year,
$SUErank_{t,i}$–the SUE-based decile of the firm as of the fourth fiscal quarter-end during the year in which the F-score is calculated. SUE is defined as the seasonal change in quarterly net income scaled by average balance sheet total assets.
$Glamour_{t,i}$–dummy variable = 1 if the firm falls into b/m deciles (1–3) and 0 otherwise,
$Value_{t,i}$–dummy variable = 1 if the firm falls into b/m deciles (8–10) and 0 otherwise.