Fundamental Strength and Short-Term Return Reversal

Zhaobo Zhu

Licheng Sun

Min Chen*

First Draft: December 2016

This Version: January 2019

---

* Zhu, zb.zhu@szu.edu.cn, Shenzhen Audencia Business School – Shenzhen University, Shenzhen 518060, China, and Audencia Business School, Nantes 44300, France; Sun, lsun@odu.edu, Department of Finance, Strome College of Business, Old Dominion University, Norfolk, VA 23529, USA; Chen, mchen11@sfsu.edu, Department of Accounting, College of Business, San Francisco State University, San Francisco, CA 94132, USA. We thank seminar participants at the 2018 Financial Management Association annual meeting, Shenzhen Audencia Business School, Old Dominion University, and San Francisco State University, Karl Diether at Brigham Young University, and an anonymous referee for helpful comments.

Fundamental Strength and Short-Term Return Reversal

Abstract

We document that the fundamental strength (FSCORE) of a firm exerts a significant influence on the performance of short-term reversal strategies. Past losers with strong fundamentals significantly outperform past winners with weak fundamentals. Our FSCORE approach is complementary to Da, Liu, and Schaumburg's (2014) cash flow news metrics based on analysts' forecast revisions in that many firms do not have analyst following. Our approach also seems capable of capturing the lagged effects from past fundamental news shocks. After controlling for fundamental strength, we find that investor sentiment plays a more dominant role than do liquidity shocks in explaining return reversal.

Keywords: short-term return reversal; fundamental strength; analyst forecast revision; slow incorporation of information

JEL Classification: G11, G12, G14

1. Introduction

"*It's far better to buy a wonderful company at a fair price than a fair company at a wonderful price.*"

— Warren Buffett, Berkshire Hathaway Chairman's Letter (1989)

Contrarian investors such as Warren Buffett often preach that the average investor should buy companies with solid fundamentals at bargain prices. In other words, a sound contrarian investment strategy should take into consideration two variables: price and fundamental value. In his classic book, *The Intelligent Investor* (p. 42), Benjamin Graham explains the intertwining relation between the two variables as follows: "Basically, price fluctuations have only one significant meaning for the true investor. They provide him with an opportunity to buy wisely when prices fall sharply and to sell wisely when they advance a great deal. At other times, he will do better if he forgets about the stock market and pays attention to his dividend returns and to the operating results of his companies."

Notwithstanding the prominent role accentuated by these legendary investors on fundamental value, the extant academic literature on contrarian (or equivalently reversal) strategies primarily focuses on price-based reversal strategies and, in many cases, jettisons information obtained from fundamental analysis. As an example, consider the short-term reversal in stock returns, a well-established anomaly that appears to contradict the weak-form market efficiency. Using monthly returns from 1934 to 1987, Jegadeesh (1990) documents that an equally weighted portfolio that buys losers and sells winners from the past one-month horizon earns an average return of approximately 2% per month. Using weekly stock returns, Lehmann (1990) and Cooper (1999) also report similar findings.

A seemingly plausible explanation of the short-term reversal anomaly is investor overreaction. For instance, Lehman (1990) hypothesizes that (p. 2) "the predictability of equity returns may reflect the overreaction of stocks prices, `fads', or the cognitive misconception of investors in an inefficient market."

Another possibility is that short-term reversal is driven by transient liquidity shocks. For example, Grossman and Miller (1988) and Campbell, Grossman, and Wang (1993) present models where return reversals could result from the market makers' accommodation of the noise traders' order flows. These authors show that risk-averse market makers will demand a higher expected return when providing liquidity to noninformational liquidity shocks. Many empirical studies (e.g., Jegadeesh and Titman, 1995; Conrad, Gultekin, and Kaul, 1997; and more recently Cheng, Hameed, Subrahmanyam, and Titman, 2017) appear to support this liquidity-trading hypothesis.

In an insightful paper, Da, Liu, and Schaumburg (2014) (hereafter DLS) point out that to better understand the impact from investor sentiment and liquidity shocks on short-term reversals, it is imperative that researchers first isolate their effect from that of fundamental news. Using analysts' forecast revisions as a proxy for cash flow news, they find that an enhanced reversal strategy based on residual returns is four times as profitable as the standard short-term reversal strategy. Echoing DLS's findings, Hameed and Mian (2015) propose an intra-industry reversal strategy. The idea is that firms in the same industry are subject to the same technological, regulatory, and macroeconomic shocks. Therefore, reversal strategies based on industry-adjusted returns are more likely to capture deviations from fundamental values.

In this paper, we study the impact of fundamental news on short-term return reversals by using an alternative measure of fundamental information — the FSCORE metric proposed by

Piotroski (2000) and Piotroski and So (2012). The FSCORE approach has at least three advantages. First, the FSCORE approach is a comprehensive metric of a firm's fundamental strength. The FSCORE synthesizes information from nine signals along three dimensions of a firm's financial performance: profitability, the change in financial leverage and liquidity, and the change in operational efficiency. Second, circumventing possible measurement error problems, the required fundamental information is gathered directly from financial statements. Last, but not the least, the FSCORE approach is a nonparametric measure. Compared with a parametric approach, it is more robust and helps alleviate concerns over potential estimation biases.

We emphasize that the FSCORE approach is complementary to DLS's approach that employs cash flow metrics based on the analysts' forecast revisions. It is well known that analysts tend to only follow relatively large companies. By comparison, the use of the FSCORE approach is unconstrained by firm size. For example, we find that in our sample, depending on the specific choice of cash flow news metrics, about one third to one half of the firms in our sample are not covered by one of the DLS cash flow news proxies.

Furthermore, the use of FSCORE as a measure of fundamental strength also allows us to go beyond DLS's findings. We find that short-term reversal strategies that are consistent with a firm's fundamental strength significantly outperform those that are not. For example, when double-sorting firms on past 1-month returns and their FSCORE, the reversal strategy that is long (short) past 1-month losers (winners) with high (low) FSCORE earns an average monthly return of 1.82% with a *t*-statistic of 6.03, which is nearly four times the average return earned by the standard unconditional reversal portfolio (0.50% with a *t*-statistic of 2.56) in our sample. Importantly, this finding holds even after controlling for the DLS cash flow measures.

We conjecture that our results are likely due to the existence of a lag effect for the incorporation of fundamental news into prices. Piotroski (2000) finds that the FSCORE approach is most useful among small and medium-sized firms, companies with low share turnover, and firms with no analyst following. Consequently, Piotroski attributes the predictive power of the FSCORE to investor underreaction to historical financial statement information. Choi and Sias (2012) provide a more formal test of this slow incorporation of information hypothesis. Consistent with this hypothesis, they show that sophisticated institutional investors respond to financial strength signals before less sophisticated institutional investors. In addition, the financial strength (FSCORE) can predict both future returns and future institutional demand, and institutional demand drives prices. Taken together, the slow incorporation of information hypothesis explains why controlling only for current cash flow news (as in the DLS study) might not be enough. We also need to account for the lagged impact from past fundamental news, which in turn explains the empirical relation between fundamental strength and short-term reversal.

Our results withstand a battery of robustness tests, such as the use of industry-adjusted returns, different subperiod samples, and non-January months. The results remain intact after controlling for stock characteristics, bid-ask spreads, transaction costs, as well as the release of public fundamental information in the portfolio formation month.

Recent empirical evidence indicates that the unconditional short-term reversal strategy has weakened substantially in the post-2000 era (e.g., Stivers and Sun, 2013; Chordia, Subrahmanyam, and Tong, 2014). As a result, several interesting papers have proposed new and refined short-term reversal trading strategies (e.g., Da, Liu, and Schaumburg, 2014; Hameed and Mian, 2015; Cheng, Hameed, Subrahmanyam, and Titman, 2017). Our paper joins these papers by showing the importance of accounting for the role of financial strength when constructing enhanced reversal trading strategies.

This paper is organized as follows. Section 2 discusses the implications of the slow incorporation of information hypothesis on the relation between financial strength and short-term reversal under the DLS residual returns framework. Section 3 describes the data that are employed in this study. Section 4 presents our main empirical results, and section 5 addresses issues related to transaction costs. We offer some concluding remarks in section 6.

2. Slow Incorporation of Information, Financial Strength, and Short-Term Reversal

DLS (2014) propose the construction of short-term reversal portfolios using residual returns, which is defined as:

$$Residual_{t+1} = r_{t+1} - u_t - CF_{t+1}, \tag{1}$$

where r_{t+1} denotes the realized return for a given firm, u_t denotes the conditional expected return[1], and CF_{t+1} denotes the cash flow news. The key idea from DLS is that residual returns are more likely to reverse, as they are prone to impacts from investor sentiment and liquidity shocks after we isolate the influence from fundamental news. In this equation, note that the lagged values of cash flow news do not emerge, as DLS implicitly assume that past fundamental information has already been incorporated into the current stock prices.

However, at least for some firms, such as small to medium-sized firms and firms with zero or only irregular analyst coverage, Piotroski (2000) and Hong, Lim, and Stein (2000) show that

[1] DLS rely on the Fama-French three-factor model to estimate the conditional expected return. They also note that their results are robust to different benchmark models.

the incorporation of fundamental information into prices could be quite slow. Hong and Stein (1999) present a theoretical model where the slow diffusion of fundamental information triggers subsequent price momentum. Using institutional demand data, Choi and Sias (2012) confirm that the predictive value of the FSCORE arises from the gradual incorporation of fundamental news. Based on these findings[2], we propose the following modification to equation (1) to account for the slow incorporation of fundamental news:

$$Residual_{t+1} = r_{t+1} - u_t - \frac{1}{n}\sum_{k=0}^{n-1} CF_{t-k+1}, \tag{2}$$

where the last term signifies that it could take up to *n* periods for the cash flow news to be fully incorporated into prices. We note that the parameter *n* controls the speed of the incorporation of information into prices. The two equations are the same when n = 1, which could be a reasonable parameter value for large companies with sufficient analyst coverage. For such firms, it is likely that fundamental news is incorporated into prices in a timely and efficient manner. However, for firms where our measure of fundamental strength (FSCORE) has predictive power, it appears reasonable to assume that *n* is greater than 1.

DLS (2014) describe in some detail how to compute *CF*, the cash flow news variable, based on the analysts' forecast revisions. However, for firms where equation (2) is more applicable, this approach is not available because many such firms are not followed by analysts. Hence, for our purpose, we rely on the FSCORE to categorize firms based on the nature of past fundamental news: high (low) FSCORE firms represent those receiving a series of positive (negative) fundamental news.

[2] Later, in table 2, we confirm the predictive power of the quarterly FSCORE used in our sample.

Thus, under the slow incorporation of information hypothesis, equation (2) predicts that the short-term reversal strategy that is long (short) past losers (winners) with high (low) FSCORE should outperform other reversal strategies that do not exploit this fundamental information. To see this prediction more clearly, we can rewrite equation (2) in terms of the adjusted return $r_{t+1} - u_t$, which is equal to the combination of the residual return and the sum of past cash flow news. Since the residual return is negatively correlated with the past 1-month return, and past cash flow news is positively correlated with the FSCORE, the portfolio that is long in past losers and high FSCORE firms can earn a positive adjusted return, and *vice versa*. In table 1, based on the slow incorporation of information hypothesis, we summarize the predicted signs of these adjusted returns.

Motivated by Stein (2009), we define the *fundamental-anchored reversal* (FAR) strategy as the short-term reversal strategy that takes a long position in past losers with high FSCORE and simultaneously a short position in past winners with low FSCORE. Similarly, we define the *fundamental-unanchored reversal* (FUR) strategy as one that takes a long (short) position in past losers (winners) with low (high) FSCORE. As seen from table 1, the slow incorporation of information hypothesis predicts that the FAR strategy should be unambiguously profitable but that the fate of the FUR strategy is uncertain. We test these predictions with portfolios double-sorted on past 1-month returns as well as on the FSCORE metric.

3. Data

Our sample consists of common stocks (share code 10 or 11) listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and National Association of Securities Dealers Automated Quotations (NASDAQ) from April 1984 to December 2015. Stock information such as stock price, trading volume, shares outstanding, and industry codes are from the Center for Research in Security Prices (CRSP). Financial statement data are from the Compustat database. The Analyst consensus earnings forecasts are obtained from the Institutional Brokers Estimate System (I/B/E/S) database. To alleviate concerns about market microstructure related biases, stocks with prices less than $5 at the end of the portfolio formation period are excluded. Fama-French factors data are obtained from Kenneth French's website. Investor sentiment data are obtained from Jeffrey Wurgler's website.[3] Following Shumway (1997) and Shumway and Warther (1999), we set delisting returns of -30% to NYSE/AMEX delisted stocks and -50% to NASDAQ delisted stocks if their delisting returns are missing or zero and if the delisting is due to performance reasons.

We rely on the FSCORE metric first proposed by Piotroski (2000) to measure a firm's fundamental strength. In the existing literature, the FSCORE has been widely utilized to measure the firms' financial/fundamental strength (Piotroski, 2000; Fama and French, 2006; Piotroski and So, 2012; Choi and Sias, 2012). The FSCORE is an aggregate index that is based on "nine binary signals designed to measure three different dimensions of the firm's financial condition: profitability, change in financial leverage/liquidity, and change in operational efficiency" (Piotroski and So, 2012, p. 2870). The range of the FSCORE is from zero to nine points. Each signal is equal to one (zero) point if the signal indicates a positive (negative) financial performance. Specifically, a firm scores one point if it has realized (i) a positive return-on-assets (ROA), (ii) a positive cash flow from operations, (iii) a positive change in ROA, (iv) a positive difference between net income and cash flow from operations (Accrual), (v) a decrease in the ratio of long-term debt to total assets, (vi) a positive change in the current ratio, (vii) no issuance

3 We thank these authors for generously providing their data.

of new common equity, (viii) a positive change in the gross margin ratio, or (ix) a positive change in the asset turnover ratio. A more detailed description can be found in the Appendix of Piotroski and So (2012).

Each month, we match monthly stock return data with the most recently available quarterly FSCORE. To illustrate, if a firm's fiscal year-end month is December of year t-1 and the portfolio formation month is January of year *t*, then the latest financial statement information we use is the third quarter (Q3) financial statement report in year t-1 because the fourth quarter financial report for year t-1 is not available to public investors at the end of January in year t.

The SEC requires domestic public firms to file quarterly and annual financial reports in 45 and 90 days, respectively.[4] For accelerated filers/large accelerated filers, the SEC requires them to file quarterly and annual financial reports in 40 and 75/60 days, respectively. We allow a 2-month information lag between the first three quarterly financial reports and the portfolio formation end date and a 4-month lag between the fourth (annual) quarterly financial reports and the portfolio formation end date. Fama and French (1992) document that approximately 20% of firms do not strictly comply with the SEC requirements. Piotroski and So (2012) allow a 4-month lag between the annual financial reports and the portfolio formation date. A 2-month lag between the first three quarterly financial reports and the portfolio formation end date is reasonable because a 10-Q is easier to file than a 10-K and most firms tend to file on time. A 4-month lag between the fourth quarterly (annual) financial reports and the portfolio formation end date is also reasonable mainly because of the following reasons: (i) there is evidence that the majority of these late filers are penny stocks (recall that we exclude stocks trading below five

[4] See the SEC website for detailed specific requirements: http://www.secfile.com/our-resources/secdeadline/, https://www.sec.gov/rules/final/33-8128.htm#IC1.

dollars);[5] (ii) in the recent decade, under the new SEC filing rule, accelerated firms file their reports within 75 days, and non-accelerated firms should file their reports within 4 months;[6] (iii) as there are punitive actions against nontimely filers, and thus there is no incentive for firms to delay reports (Bartov, DeFond, and Konchitchki, 2015); and (iv) only one of twelve formation months is affected by the nontimely filing concern (e.g., if the fiscal year end month is December, then only the portfolio formation period of April is affected). In untabulated results, we find that our results are robust, even if we allow a 3/5-month lag for quarterly/annual reports.[7] As an additional robustness check, we also use the Report Date of Quarterly Earnings (RDQ) to identify the most recently available fundamental information.

4. Main Results

4.1 Fundamental Strength and Return Predictability

For the slow incorporation of fundamental information hypothesis to hold, the FSCORE should possess some predictive power for future returns. Piotroski (2000) is probably the first to show the predictive power of the annual FSCORE. Here, we examine the return predictability by using the quarterly FSCORE. Table 2 presents the raw and market-adjusted returns of portfolios with different quarterly FSCOREs. We report that the FSCORE can successfully predict returns for the next two quarters. Firms with low (high) FSCOREs experience low (high) future returns.

5 According to Audit Analytics, "late filings are rare" because "pink sheets filed about 85% of all NT 10-Ks issued". See http://www.auditanalytics.com/blog/hain-delays-filing-what-to-expect/.

6 SEC rule 12b-25 requires that for a non-timely 10-K (10-Q), a late filing notification provides an additional 15 (5) days for the actual 10-K (10-Q) to be filed. Under the new 60/75-day rules for LAF/AF, it is possible that many accelerated (non-accelerated) filers file in 3 (4) months, even though they file the notification for non-timely 10-Ks (10-Qs).

7 These results are available from authors upon request.

Moreover, the positive relation between the FSCORE and future returns is monotonic. Following Piotroski and So (2012), we classify a firm as a fundamentally strong firm, a fundamentally middle firm, and a fundamentally weak firm if the firm's FSCORE is greater than or equal to seven (7-9), between four and six (4-6), or less than or equal to three (0-3), respectively. On average, in the subsequent month, fundamentally strong firms significantly outperform fundamentally weak firms by 1.2%. The outperformance is 1.07% (0.96%) per month in the subsequent one (two) quarter(s). These results confirm the predictive power of the quarterly FSCORE and are consistent with earlier findings that the annual FSCORE can predict future returns, even after controlling for size, book-to-market ratio, and asset growth (Piotroski, 2000; Fama and French, 2006; Piotroski and So, 2012).

4.2 The Interaction of Past 1-Month Returns and Fundamental Strength

In this subsection, we implement the portfolio approach to test the predictions listed in table 1. We form 15 equal-weighted portfolios (5 past return quintiles and 3 FSCORE ranks) with independent sorts on the past 1-month (1M) returns and fundamental strength measured by the quarterly FSCORE.

Table 3 presents the average monthly raw returns and risk-adjusted returns of these portfolios. There are several important findings. First, across all five reversal portfolios, the quarterly FSCORE significantly differentiates future winners from losers. Specifically, 1M losers (winners) with strong fundamental strength significantly outperform 1M losers (winners) with weak fundamental strength by 1.39% (1.2%) each month.

Second, within each FSCORE rank, the loser minus winner reversal portfolios also earn a significantly positive return. The average monthly returns (t-statistics) are 0.43% (1.70), 0.60%

(3.11), and 0.62% (2.63) for low, middle, and high FSCORE ranks, respectively. We note that these reversal portfolio returns are comparable to the unconditional average reversal portfolio return of 0.50% in our sample. This demonstrates that after controlling for fundamental strength, sentiment or liquidity-driven trading dominates the short-term reversal.

To shed light on the predictions from table 1, we examine the average returns of the FAR and FUR portfolios (as defined in section 2). We find that the FAR portfolio earns a highly significant average monthly return of 1.82% (t-statistic = 6.03). In contrast, the FUR portfolio has an average return of -0.77% (t-statistic = -3.07). Taken together, these results support the hypothesis that short-term reversals are affected not only by sentiment and liquidity-related trading but also by past fundamental news due to the slow incorporation of fundamental information.

Next, we present results based on the risk-adjusted returns. We consider three benchmark asset pricing models. First, we use the Fama and French (1993) 3-factor model (FF3), where the three pricing factors are market, size (SMB), and value (HML). Second, we augment the Fama and French 3-factor model with two additional factors (FF3MR): momentum and short-term reversal. Both factors are from Ken French's website. Third, we use the recently proposed Fama and French (2016) 5-factor model (FF5), which adds a profitability (RMW) factor and an investment (CMA) factor to the original three-factor model. We report that our results are robust to the use of the risk-adjusted returns, regardless of the underlying benchmark models. For the FAR portfolio, the risk-adjusted returns are 1.64% (FF3), 1.42% (FF3MR), and 1.31% (FF5), with corresponding t-statistics of 5.42, 6.59, and 4.28, respectively. For the FUR portfolio, the risk-adjusted returns are all negative and significant. Thus, we conclude that our results based on risk-adjusted returns are consistent with those based on raw returns.

Finally, following Hameed and Mian (2015), we also implement industry-based short-term reversal strategies. Following Fama and French (1997), we classify firms into 17 industries based on the firms' 4-digit standard industrial classification (SIC) codes. We report that the industry-based results are very similar to the firm-level results. For example, the industry-based FAR strategy (1.94%) significantly outperforms the industry-based simple reversal strategy (0.62%). In contrast, the industry-based FUR strategy suffers from a significantly negative average monthly return of -0.68%. These findings suggest that our results remain intact after controlling for the industry effect documented in Hameed and Mian (2015).

4.3 Regression Analysis

Avramov, Chordia, and Goyal (2006) and Cheng, Hameed, Subrahmanyam, and Titman (2017) find that when studying short-term return reversals, it is important to control for firm characteristics that are known to explain cross-sectional expected returns. Following these authors, we run the following Fama-MacBeth (1973) cross-sectional regression model:

$$\begin{aligned} R_{i\,t+1} = {} & \beta_1 Winner_{i\,t} + \beta_2 Winner_{i\,t}{*}LowFSCORE_{i\,t} + \beta_3 Winner_{i\,t}{*}MidFSCORE_{i\,t} \\ & + \beta_4 Middle_{i\,t} + \beta_5 Middle_{i\,t}{*}LowFSCORE_{i\,t} + \beta_6 Middle_{i\,t}{*}HighFSCORE_{i\,t} + \\ & \beta_7 Loser_{i\,t} + \beta_8 Loser_{i\,t}{*}MidFSCORE_{i\,t} + \beta_9 Loser_{i\,t}{*}HighFSCORE_{i\,t} + \gamma' CV + \varepsilon_{i\,t+1}, \end{aligned} \tag{3}$$

where, following Piotroski and So (2012), the intercept item is suppressed to avoid collinearity in the model and *CV* denotes a vector of control variables including size, book-market ratio (BM), momentum, volatility, illiquidity, and turnover, which are assigned to deciles with a value ranging from one to ten.[8] The indicator variables Winner, Middle, and Loser are set to one if the stock's return in the formation month is in the top 20%, middle 60%, and bottom 20% of all sample stocks, respectively. The variables LowFSCORE, MidFSCORE, and HighFSCORE are set to one if the firm's FSCORE is less than four (0-3), between four and six (4-6), or greater than six (7-9), respectively. The interaction terms, such as Winner*LowFSCORE and Loser*HighFSCORE, capture the inconsistency between the past 1-month returns and fundamental strength.

Table 4 reports the estimated coefficients of interest. Consistent with results from Table 3, 1M winners with weak fundamental strength significantly underperform 1M winners with strong fundamental strength (as indicated by the significant negative coefficients of Winner*LowFSCORE across all model specifications), and 1M losers with strong fundamentals significantly outperform 1M losers with weak fundamentals (as indicated by the significant positive coefficients of Loser*HighFSCORE). Therefore, we find that after accounting for all the control variables with known explanatory power, the FAR strategy still significantly outperform the FUR strategy (as indicated in Model 5).

In summary, the results from both the portfolio analysis (Table 3) and the regression analysis (Table 4) confirm that researchers need to account for the impact from fundamental information as manifested in the FSCORE variable. Since the FSCORE reflects historical financial statement information, our findings are consistent with the slow incorporation of fundamental information. We find that the short-term reversal strategy that exploits such fundamental information (namely, the FAR strategy) delivers far more superior performance

[8] We find similar results when using the untransformed data for these control variables.

than do strategies that either ignore or go against the fundamental trend (such as the FUR strategy).

4.4 Comparison with Da, Liu, and Schaumburg's (2014) Cash Flow News Metrics

In table 5, we directly test if our FSCORE-based results will hold in the presence of DLS's metrics of cash flow news. Based on the analysts' earnings forecast revisions, DLS construct two measures of cash flow news. First, these authors rely on FREV, which is a simple proxy for cash flow news and is computed as the analysts' forecast revisions scaled by book value per share in months where there are no earnings announcement or (scaled) by earnings surprises when there is an earnings announcement. Second, DLS also propose a more complicated measure of cash flow news; we denote this measure as CF, and it takes into account multiple earnings forecasts for different maturities. For a detailed description of the CF measure, we refer readers to the DLS study.

In panel A of table 5, we perform a triple sort on past 1M returns, FREV, and the FSCORE. To ensure that we have a sufficiently large number of stocks in each portfolio, we use tercile breakpoints for all three sorting variables. We find that among low FSCORE firms, the short-term reversal strategy implemented on firms with poor cash flow news (FREV1) earns a positive return of 0.82%. However, neither one of the two legs (long or short) is significant. Interestingly, we also find that among firms with good cash flow news (FREV3), the short-term reversal strategy is unprofitable, as both legs of the strategy earn positive profits with similar magnitudes. The results among high FSCORE firms are also quite similar with more significant t-statistics. The finding confirms that FREV behaves similarly to FSCORE, in that strong cash flow news boosts the returns of both past losers and winners.

To help differentiate the hypotheses, we focus on four portfolios that are of special interest. Portfolios A, B, C, and D consist of firms that are low-FSCORE/FREV3/1M losers, low-FSCORE/FREV1/1M winners, high-FSCORE/FREV3/1M losers, and high-FSCORE/FREV1/1M winners, respectively. Therefore, the spread portfolio (A-B) that is long A and short B is the FAR portfolio implemented within the low-FSCORE subsample. Similarly, Portfolio (C-D) is the FAR portfolio within the high-FSCORE subsample. Portfolio (C-B) is the FAR portfolio where the fundamental news as measured by FREV and the FSCORE are consistent with each other. Portfolio (A-D) is the FAR portfolio where the FSCORE is high but the cash flow news as measured by FREV is poor. We find that both portfolios (A-B) and (C-D) are profitable. The average returns are 1.20% and 1.64%, respectively. The most profitable strategy is portfolio (C-B), with a highly significant average return of 2.27%. Recall that this is the case where the fundamental news from FREV and the FSCORE are consistent. In contrast, when the FSCORE and FREV are inconsistent, the reversal strategy (A-D) is only marginally profitable (0.58%).

In panel B of table 5, we replace FREV with CF, the more complicated metric of cash flow news proposed by DLS. Overall, the results are very similar to those reported in panel A, with the exception that the average return for portfolio (A-D) is only 0.22% and is statistically insignificant. We conclude that while both the FSCORE and the two measures of cash flows news contain useful fundamental information and perform similarly, the FSCORE does appear to have the upper hand, especially in comparison with the CF variable. Additionally, note that these results from table 5 likely favor the cash flow news metrics because we have to use a sample where both FSCORE and the analysts' forecasts are available. Recall that the FSCORE likely works best among firms where the analysts' forecasts are unavailable. In our view, the results from table 5 appear to support the slow incorporation of information hypothesis.

4.5 Robustness Tests

Table 6 reports the results from a battery of robustness tests. To conserve space, we only report the performance of the standard, fundamental-anchored, and fundamental-unanchored short-term reversal strategies. We verify that our main results survive these robustness checks.

4.5.1 January Seasonality

Jegadeesh (1990) documents that short-term return reversals are strongest in January possibly due to tax-loss selling. We are interested in knowing whether the success of the FSCORE in enhancing short-term reversals is sensitive to the January effect. Panel A of table 6 reports the performance of three strategies in non-January months. The FAR strategy generates a significant average monthly raw return of 1.64%, while the standard and FUR strategies generate only 0.25% and -1.05%, respectively. We also find (in untabulated results) that the FAR (FUR) strategy generates a significant average monthly raw return of 3.88% (2.39%) in January. These results indicate that our results are not driven by the January effect.

4.5.2 Subperiods

Panel B of table 6 reports the performance of the fundamental-based reversal strategies in the two sub-periods. From 1984 to 1999, the FAR strategy generates a significant average monthly raw return of 2.29%, while the standard and FUR strategies generate only 0.52% and -1.02%, respectively. From 2000 to 2015, the FAR strategy still generates a significant average monthly raw return of 1.35%, while the standard and FUR strategies generate only 0.48% and -

0.52%, respectively. Even though the FAR strategy performs better in the earlier period, the strategy still generates economically and statistically significant profits after 2000. The results based on risk-adjusted returns are also very similar.

4.5.3 Alternative Classification of Fundamentally Strong/Weak Firms

In the main analysis, following Piotroski and So (2012), a firm's fundamental strength is defined as strong if the firm's FSCORE is greater than six points (7-9); a firm's fundamental strength is defined as weak if its FSCORE is less than four points (0-3); and a firm's fundamental strength is defined as middle if its FSCORE is between four and six (4-6). In this subsection, we examine if our results are sensitive to the definition of strong/weak fundamental strength. Panel C reports the results for an alternative definition of strong/weak fundamental strength.

In the first alternative definition, a firm's fundamental strength is strong only if the firm's FSCORE is greater than seven points (8-9), and the fundamental strength is weak only if FSCORE is less than three points (0-2). The FAR (FUR) reversal strategy generates an average monthly raw return of 2.05% (-1.08%), compared to that of 1.82% (-0.77%) in the main analysis. In the second alternative definition, a firm's fundamental strength is strong if the firm's FSCORE is greater than five points (6-9), and the fundamental strength is weak only if FSCORE is less than five points (0-4). The FAR (FUR) strategy generates an average monthly raw return of 1.55% (-0.47%). These results suggest that the difference between the fundamental-anchored and fundamental-unanchored reversal strategies becomes larger when applying a more stringent criterion for the firms' fundamental strength. Overall, we find that our results are not particularly sensitive to these alternative definitions of fundamental strength.

4.5.4 Annual FSCORE

Piotroski (2000) and Piotroski and So (2012) use the annual FSCORE to dissect the value/glamour effect due to the low frequency of the value/glamour strategy. However, because of the relatively higher frequency of the short-term reversal strategy, we adopt the quarterly FSCORE approach when presenting our main results. In panel D of table 6, using the annual FSCORE, we stress test our results.

Following Piotroski and So (2012), we use a 4-month gap between the most recently available annual financial statement reports and the end of the formation period. Our results show that the FAR (FUR) strategy generates an average monthly raw return of 1.31% (-0.1%) by using an annual FSCORE and an average monthly raw return of 1.82% (-0.77%) by using a quarterly FSCORE. This finding is consistent with notion that strategies based on "real-time" information should perform better than strategies relying on "stale" information. However, the fact that our results are robust to the use of an annual FSCORE provides further support for the slow incorporation of information hypothesis.

4.5.5 Bid-Ask Effect

Some studies document that the bid-ask spread could significantly explain most of the short-term reversal profits (Jegadeesh and Titman (1995), Conrad et al. (1997)). However, Hameed and Mian (2015) show that, after considering the bid-ask spread effect, intra-industry reversal strategies still generate significant profits. We examine if the bid-ask spread significantly affects the fundamental-based reversals. Following Jegadeesh (1990) and Hameed and Mian (2015), we skip the first day in the holding period. Panel E of table 6 reports the results. We find that, compared to the standard reversal strategy, which generates an average monthly raw return of 0.19%, the FAR (FUR) strategy generates an average monthly raw return of 1.35% (-0.9%). These results indicate that the bid-ask spread cannot be the main source of profitability for short-term reversals and that our results are not due to market microstructure-induced biases.

4.5.6 Real-Time Fundamental Information Based on RDQ

Our main results rely on a four-month (two-month) gap to match price data and annual (quarterly) financial statement reports, which is a common practice adopted in many prior studies. To better match trading data and publicly available fundamental information, a potentially more interesting approach is to use the RDQ (Report Date of Quarterly Earnings) to identify the real-time fundamental information available to investors. The merit of matching based on the RDQ is that this approach can effectively avoid data error due to mismatch. However, the downside is that because of missing RDQ data, researchers suffer from losing some data points. Panel F of table 6 reports the robustness results based on the RDQ data. We find that the differences in the returns of simple, fundamental-anchored, and fundamental-unanchored reversal strategies are minimal across the two/four-month gap sample and the RDQ sample. This comparison suggests that our main results based on the simple two/four-month rule are very robust.

4.5.7 Gross-Return Weighted Portfolios

The results presented so far are based on equal-weighted portfolios. While this is a reasonable approach, as the FSCORE should work better among small firms in accordance with the slow incorporation of information hypothesis, a reasonable concern is that these findings might be exaggerated due to market microstructure biases. Hence, to correct for the potential upward bias, we follow the methodology of Asparouhova, Bessembinder, and Kalcheva (2013) and compute our results using gross-return weighted portfolios. We report these results in panel

G of table 6. We find that our new results are very close to those based on equal-weighted portfolios. For example, the FAR (FUR) portfolio earns a highly significant month raw return of 1.86% (-0.77%). Thus, we conclude that the adoption of gross-return weighted portfolios does not affect our findings.

4.5.8 Industry-adjusted Value-weighted Portfolios

It is also interesting to determine if our results are robust when using value-weighted portfolios. Following Hameed and Mian (2015) and DLS (2014), we control for the industry effect. The results are reported in panel H of table 6. Consistent with the slow diffusion of information hypothesis, we find that when using value-weighted portfolios, which are dominated by large firms, the FSCORE-based reversal strategies are less profitable. For example, the FAR (FUR) portfolio earns a month raw return of 0.92% (-0.47%), with a t-statistic of 2.91 (-1.54). Overall, these results confirm the interpretation that the FSCORE proxies for past fundamental news shocks, which can only be slowly incorporated into prices among small firms.

4.5.9 Stock Characteristics

Previous studies document that standard short-term reversals are stronger among stocks with some specific characteristics. For example, standard short-term reversals are stronger among small, illiquid, and heavily traded stocks (e.g., Avramov et al. (2006)). To investigate the robustness of our findings, we examine the performance of the FAR strategies within stock subsamples based on specific stock characteristics. The criteria for the size of a subsample are based on the top and bottom 40% of firms with any firm characteristics in the formation month.

Panel A of table 7 reports the performance of fundamental-based reversal strategies within subsamples of large and small stocks. Small (large) stocks are those in the bottom (top) 40% of all sample stocks in terms of market capitalization at the end of the formation month. We report that the FAR strategy experiences an average monthly raw return of 2.42% (0.95%) among small (large) stocks. The performance difference between small and large stocks is pronounced, which is consistent with the slow incorporation of information hypothesis. However, we find it reassuring that our fundamental-based reversal strategy even works well among large stocks.

Panel B of table 7 reports the results for subsamples of low and high volatility stocks. Since higher return volatility implies higher inventory risk for market makers who provide liquidity, we expect stronger reversals among highly volatile stocks. As expected, we find that the FAR strategy performs better among high-volatility stocks. It earns an average monthly raw return of 2.16% (1.41%) among high (low) volatility stocks. The risk-adjusted results are similar.

Panel C of table 7 reports the results for subsamples of liquid and illiquid stocks. Avramov et al. (2006) show that the standard short-term reversal is concentrated among illiquid stocks. Following Avramov et al. (2006), we use the Amihud (2002) illiquidity measure to measure the stock's illiquidity. As expected, we find that the FAR strategy generates higher profits among illiquid stocks. The fundamental-based reversal strategy experiences an average monthly raw return of 2.62% (1.11%) among illiquid (liquid) stocks. Moreover, the difference in performance between the FAR strategy and the FUR strategy is more pronounced among illiquid stocks.

Panel D of table 7 reports the results for subsamples of high- and low-turnover stocks. Avramov et al. (2006) show that short-term reversals are stronger among high-turnover stocks, but Cooper (1999) document a negative relation between trading volume and return reversals among large NYSE stocks. We find that the FAR strategy generates higher profits among low-turnover stocks, consistent with Cooper (1999). Note that Avramov et al. (2006) use a price screen of 1 dollar to filter out penny stocks, but we use a more stringent filter of five dollars.

4.6 The Effect of Public Fundamental Information Announcements

Nagel (2012) argues that return reversals are weakened following the arrival of public fundamental information because past returns contain much fundamental information (that is, less nonfundamental shocks). Hameed and Mian (2015) provide some empirical evidence on Nagel's argument in the context of intra-industry reversals.

In this subsection, we examine whether the FAR strategy can survive the announcement effect of public fundamental information. We use the quarterly earnings announcements (Report Date of Quarterly Earnings - RDQ) to identify the arrival of public fundamental information. Specifically, we divide all observations into two groups: the RDQ group where the report date of the quarterly earnings is in the reversal portfolio formation month and the non-RDQ group where there is no quarterly earnings announcements in the formation month. The logic is that if the quarterly earnings report is announced in the formation month, a large portion of the extreme past return in the formation month is likely to stem from the fundamental information. In contrast, if there is no announcement of quarterly earnings in the formation month, a large portion of extreme past return is likely to be driven by nonfundamental liquidity shocks.

Table 8 reports the results. First, we find that all standard and conditional short-term reversal strategies experience stronger reversals in the non-RDQ subsample than in the RDQ subsample. The standard (decile) reversal strategy generates an average monthly raw return of 1.07% (-0.32%) in the non-RDQ (RDQ) subsample. The FAR strategy generates an average monthly raw return of 2.28% (1.04%) in the non-RDQ (RDQ) subsample. The difference in performance between the RDQ and the non-RDQ sample is economically and statistically significant. These results confirm our finding that the speed at which prices incorporate fundamental information can influence the short-term reversal. In particular, the public announcement of fundamental information in the RDQ sample speeds up information diffusion. Therefore, it is not surprising that the FAR strategy has a smaller profit in this sample. However, the fact that this strategy remains profitable even after the relevant information has been publicly announced is a strong endorsement of the slow diffusion of information hypothesis. The evidence from industry-based results is supportive of this conclusion.

4.7 Sentiment, Liquidity, and Fundamental-Based Reversals

In this subsection, we explore the impact on both standard and fundamental-anchored short-term reversals from variables that proxy for either liquidity or investor sentiment. Under the liquidity-based explanation, prior studies find that short-term reversals are stronger following a negative or volatile market because the cost of supplying liquidity increases due to the market makers' limited ability to supply liquidity during bad or volatile times (e.g., Brunnermeier and Pedersen, 2009; Hameed, Kang, and Viswanathan, 2010; Nagel, 2012; Hameed and Mian, 2015). DLS find that liquidity drives the reversals of recent losers and that investor sentiment drives the reversals of recent winners. Under the assumption that the FSCORE performs well in isolating the impact from fundamental news, we hope that our approach can shed light on the role of liquidity and sentiment on short-term reversals.

Specifically, we examine the following liquidity and sentiment variables: (a) DOWN market, which takes a value of 1 if the past 3-month CRSP value-weighted market index is negative and 0 otherwise (Hameed et al., 2010; Hameed and Mian, 2015); (b) *realized* market return volatility in the portfolio formation month (DLS, 2014); (c) market illiquidity computed as the difference between the average Amihud (2002) illiquidity measure and its 12-month moving average (DLS, 2014); (d) the implied volatility index (VIX) from the Chicago Board Options Exchange (CBOE); (e) Baker and Wurgler's (2006) composite sentiment index; and (f) the monthly equity share in new issues used in Baker and Wurgler (2006) (see also DLS, 2014). Following Stambaugh, Yu, and Yuan (2012) as well as the DLS study, we conduct predictive regressions to examine whether the lagged proxies for liquidity shocks and sentiment significantly predict subsequent short-term return reversals.

Table 9 reports the results. Panel A reports the estimated coefficients of proxies for market conditions for the simple short-term reversal in both the full sample as well as the non-RDQ sample. We report results for both long-short spread portfolio returns as well as the long and short legs. Consistent with findings in prior studies, the coefficients of DOWN market, market volatility, market illiquidity, and VIX are significant in almost all cases. The two sentiment variables appear to possess statistical significance mainly on the short leg (past 1-month winners).

Panel B reports the coefficients for the FAR strategy. After controlling for the fundamental strength variable, we find drastically different results from those reported in panel A. Surprisingly, we report that liquidity-related variables, such as market volatility, market illiquidity, and VIX, lose their statistical significance across the board. The most significant variable appears to be BW, the Baker and Wurgler (2006) sentiment index. The coefficients of this index are significant in all cases, except for the short leg in the non-RDQ sample. We note that the BW coefficients are positive on long legs and negative on short legs, which is consistent with the hypothesis that sentiment traders are more likely be active in the market when the overall sentiment level is high, and *vice versa*. In addition, we also report that the net share issuance variable and the DOWN market dummy both have significantly negative loadings on the short legs. This result seems consistent with investor sentiment interpretation of the DOWN market state variable (Cooper, Gutierrez, and Hameed, 2004). To sum up, we conclude that our findings are consistent with a mispricing explanation of a short-term reversal, which appears to be driven by the actions of sentiment traders. Interestingly, after controlling for fundamental news, the liquidity variables appear to have lost their explanatory power.

To provide additional robustness tests, in table 10, within various subsamples, we follow the DLS study and run time-series regressions of the excess returns of the long or short leg of the FAR portfolios on the lagged liquidity and sentiment variables. The subsamples include the top and bottom 30% stocks sorted by size, book-market ratio, Amihud illiquidity measures, and idiosyncratic volatility. The explanatory variables include the Fama-French 3 factors and the lagged values of the DOWN market dummy, realized market volatility, market illiquidity, VIX, BW sentiment index, and the net share issuance number.

We find strong support for the sentiment-based explanation. Specifically, table 10 shows that the BW sentiment index is the most significant variable. For example, it is significant and positive for the long leg excess returns across all subsample portfolios. Only two other cases are marginally significant among the long leg excess returns (VIX for small stocks and illiquidity for value stocks). On the short side, the DOWN market dummy variable appears to be the most significant, followed by net share issuance. Overall, we conclude that the evidence presented in table 10 is consistent with the results from table 9.

Stambaugh, Yu, and Yuan (2012) explore the relation between investor sentiment and a set of anomalies and find that the short leg of these anomalies are more profitable following high investor sentiment. On the surface, this finding appears to be inconsistent with our results.

However, we point out that their finding depends on two key assumptions: the presence of many well-informed investors and stocks are not undervalued (Miller, 1977). We argue that these two assumptions are unlikely to be met in the context of our paper for the following reason. The extant literature (e.g., Choi and Sias, 2012; Turtle and Wang, 2017) shows that the FSCORE anomaly is driven by the slow diffusion of information as well as investors' under-reaction to financial statement information. These findings are also consistent with the lagged cash flow news hypothesis that we adopt in our paper. Therefore, from our perspective, Miller's argument and especially his two assumptions are not applicable to our study. In fact, the anomalous returns reported by our paper are more in alignment with underpricing and the lack of well-informed investors.

To further explain the documented effect between the long leg of our trading strategy and investor sentiment, we rely on the findings by Barber and Odean (2007) and Yu and Yuan (2011). Barber and Odean (2007) find that individual investors, who are constrained by their information search ability, tend to only buy attention-grabbing stocks. However, when selling stocks, they don't have a similar search problem because they only sell stocks that they already own. Yu and Yuan (2011) find that (p. 368) "sentiment-driven investors participate and trade more aggressively in high-sentiment periods". Taken together and in the context of our paper, high (low) FSCORE firms are likely to be those that recently reported good (bad) earnings news. When this happens during the high investor sentiment period, the good news will grab investors' attention and trigger higher demand from these sentiment-driven investors. Thus, higher sentiment is associated with higher returns for the long leg. However, the short leg will not see much effect even when investor sentiment is high because of: (a) short-sale impediments, and (b) the asymmetric effect identified by Barber and Odean (2007). In other words, if sentiment-driven investors do not already own the low-FSCORE stocks, they cannot sell these stocks even if the bad news is prevalent.

5. Performance Evaluation

5.1 Transaction Costs and Sharpe Ratio

McLean and Pontiff (2016) show that the profits of many anomalies are weakened after they become public. Chordia et al. (2014) document that in the post-2000 period, short-term reversal strategies dissipated due to increasing liquidity and trading activity. Novy-Marx and Velikov (2016) show that various short-term reversal strategies do not generate profits in the presence of transaction costs. However, DLS (2014) show that the residual-based reversal strategy generates significant transaction cost-adjusted profits. We are interested in whether our fundamental-anchored reversal strategies generate profits net of transaction costs.

Table 11 reports the estimated transaction costs, net returns and Sharpe ratios. As expected, the portfolio turnover of short-term reversal strategies is very high. When estimating transaction costs, we use the *direct effective bid-ask spreads* (Chrodia, Roll, and Subrahmanyam (2000)). Lee and Ready (1991) argue that the quoted bid-ask spread may overstate the actual spread costs. Following DLS (2014), the portfolio turnover ratios and the direct effective spreads jointly provide an approximate estimate of the transaction costs. For example, the estimated transaction cost for the FAR strategy is 86.34% × 0.687 + 85.75% × 0.664 = 1.16% per month. This estimated transaction cost is economically smaller than the trading strategy's raw return of 1.82%. The non-RDQ industry-based FAR strategy earns a transaction cost-adjusted return of 1.11% per month. These results suggest that the FAR strategy is economically profitable. In contrast, simple short-term reversal and industry-adjusted reversal strategies become unprofitable after adjustments for transaction costs.

Another important criterion of portfolio performance evaluation is the Sharpe ratio. Table 11 reports the annualized Sharpe ratios of various short-term reversal strategies. The Sharpe ratios of simple and industry-based short-term reversal strategies are between 0.36 and 0.55. In contrast, the Sharpe ratios of fundamental-anchored reversal strategies are between 1.17 and 1.43. As expected, the non-RDQ industry-based FAR strategy has the highest Sharpe ratio of 1.43, suggesting that the FAR strategies are attractive in term of the risk-return tradeoff.

5.2 Transaction Cost Mitigation

Novy-Marx and Velikov (2016) argue that the transaction costs of academic anomalies are overstated because, in practice, some simple rule-based methods could reduce trading costs. For example, Groot, Huij, and Zhou (2012) and Novy-Marx and Velikov (2016) propose the buy/hold strategy, which could significantly reduce the portfolio turnover. The basic rule of the buy/hold strategy is described by Novy-Marx and Velikov (2016, pp. 122-123) as follows:

"On the long side, traders buy into a stock when it enters the buy range (e.g., highest 10% on some signal), but do not sell the stock until it falls out of the hold range, which is larger than the buy range. On the short side, traders use a more stringent threshold for shorting a stock than for maintaining a previously established short position. For example, a 10%/20% buy/hold rule implies that a trader buys stocks when they enter the top decile of the stock selection signal and holds these stocks until they fall out of the top quintile."

We examine a more conservative *fixed-time buy/hold strategy* that buys into a stock and holds it for fixed time. That is, we examine the even-time returns of trading strategies.

Table 12 reports the results. We find that various FAR strategies generate significant and positive returns in the second, third, fourth, and fifth months of the holding period. For example, the return of the non-RDQ industry-based FAR strategy in the second holding month is 1.41%, which is greater than the transaction cost-adjusted return of 1.11% shown in table 10, suggesting that holding the same group of stocks one more month is practically more profitable than rebalancing each month. In the first 4-month holding period, the cumulative buy-and-hold return of this trading strategy reaches 5.55%, which is substantially greater than the rough transaction cost of 1.27%.

For the FAR strategy, the long position includes stocks that are fundamentally strong and perform well over the past medium term; therefore, we expect these 1M losers to experience persistent good performance in subsequent months. The short position includes stocks that are fundamentally weak and perform below average over the past medium term; therefore, we expected these 1M winners to experience persistent inferior performance in subsequent months. Overall, the evidence from event-time returns supports the hypothesis of investor underreaction and the slow incorporation of information.

6. Conclusion

In this paper, we investigate the interrelation between fundamental strength and short-term reversals. Prior studies have focused primarily on the role of investor sentiment or liquidity shocks but have largely ignored the important role played by fundamental information. We adopt a nonparametric metric of fundamental strength (FSCORE) to measure the impact from past fundamental information.

Consistent with the slow diffusion of information and investor underreaction hypothesis, we report that our fundamental information metric has a persistent predictive effect on stock returns. High-FSCORE firms tend to earn much higher returns than low-FSCORE firms earn. We find significant evidence that recent losers (winners) with strong (weak) fundamental strength experience stronger reversals than do other reversal portfolio strategies. Exploiting this finding, we report that a fundamental-anchored reversal strategy could generate a highly significant average monthly return of 1.82%, which is nearly four times the profit from the unconditional reversal strategy. This finding is robust to the use of risk-adjusted returns, non-January sample, adjustments for transaction costs, the release of public fundamental information, and other robustness tests.

Isolating the (lagged) fundamental news effect with the FSCORE also enables us to investigate the root causes of short-term reversals. Prior studies find that both liquidity and investor sentiment could be contributing factors. More consistent with a mispricing interpretation, our results from tables 9 and 10 suggest that after controlling for fundamental strength, it appears that short-term reversals are mainly driven by the actions of sentiment traders.

Our results are supportive of theoretical models of investor underreaction and the slow diffusion of information (e.g., Hong and Stein, 1999). Our results are also consistent with the empirical findings from Hong, Lim, and Stein (2000), Piotroski (2000), and Choi and Sias (2012), who attribute the predictive power of the FSCORE to the slow incorporation of fundamental information into prices. From a practical perspective, the FSCORE is more readily available to the average investor than cash flow news constructed from analyst forecast revisions.

A more fundamental question is why the speed of a price adjustment to fundamental information is so slow among many firms. We conjecture that this phenomenon is probably related to the fact that the investors are constrained by their information capacity (e.g., Peng, 2005; Peng and Xiong, 2006; Cohen and Frazzini, 2008), and consequently can only pay attention to a small subset of stocks. Our future research will continue to focus on the implications of investor information capacity constraints on financial market anomalies.

Reference

Amihud, Y., 2002. Illiquidity and Stock Returns: Cross-Section and Time-Series Effects. Journal of Financial Markets. 5, 31–56.

Asparouhova, E., Bessembinder, H., Kalcheva, I., 2010. Liquidity biases in asset pricing tests. Journal of Financial Economics. 96, 215-237.

Avramov, D., ChordiaT., Goyal, A., 2006. Liquidity and Autocorrelations in Individual Stock Returns. Journal of Finance. 61, 2365-2394.

Baker, M., Wurgler, J., 2006. Investor Sentiment and the Cross-Section of Stock Returns. Journal of Finance. 61, 1645-1680.

Barber, B. M., Odean, T., 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. Journal of Finance. 55, 773-806.

Barber, B.M., Odean, T., 2007. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. Review of Financial Studies. 21, 785-818.

Bartov, E., DeFond, M. L., Konchitchki. Y., 2013. The Consequences of Untimely Quarterly and Annual Financial Reporting. Working paper, New York University.

Brunnermeier, M., Pedersen, L., 2009. Market Liquidity and Funding Liquidity. Review of Financial Studies. 22, 2201–2238.

Campbell, J. Y., Grossman, S. J., Wang, J., 1993. Trading Volume and Serial Correlation in Stock Returns. Quarterly Journal of Economics. 108, 905-939.

Cheng, S., Hameed, A., Subrahmanyam A., Titman, S., 2017. Short-Term Reversals: The Effects of Past Returns and Institutional Exits. Journal of Financial and Quantitative Analysis. 52, 143-173.

Choi, N. Y., Sias, R. W., 2012. Why Does Financial Strength Forecast Stock Returns? Evidence from Subsequent Demand by Institutional Investors. Review of Financial Studies. 25, 1550-1587.

Chordia, T., Roll, R., Subrahmanyam, A., 2000. Commonality in liquidity. Journal of Financial Economics. 56, 3-28.

Chordia, T., Subrahmanyam, A., Tong, Q., 2014. Have Capital Market Anomalies Attenuated in the Recent Era of High Liquidity and Trading Activity? Journal of Accounting Economics. 58, 41-58.

Cohen, L., Frazzini, A., 2008, Economic links and predictable returns. Journal of Finance. 63, 1977–2011.

Conrad, J., Gultekin, M., Kaul, G., 1997. Profitability of Short-Term Contrarian Strategies: Implications for Market Efficiency. Journal of Business and Economic Statistics. 15, 379–386.

Cooper, M., 1999. Filter Rules Based on Price and Volume in Individual Security Overreaction. Review of Financial Studies. 12, 901-935.

Cooper, M. J., Gutierrez Jr, R.C. and Hameed, A., 2004. Market states and momentum. The Journal of Finance. 59, 1345-1365.

Da, Z., Liu, Q., Schaumburg, E., 2014. A Closer Look at the Short-Term Return Reversal. Management Science. 60, 658-674.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under‐and overreactions. Journal of Finance. 53, 1839-1885.

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

Fama, E. F., French, K. R., 1997. Industry Cost of Equity. Journal of Financial Economics. 43, 153–193.

Fama, E. F., French, K. R., 2006. Profitability, Investment, and Average Returns. Journal of Financial Economics. 82, 491–518.

Fama, E. F., French, K. R., 2016. Dissecting anomalies with a five-factor model. Review of Financial Studies. 29, 69-103.

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

Graham, B., 1949. The Intelligent Investor. Harper & Brothers.

Groot, W. D., Huij, J., Zhou, W., 2012. Another look at trading costs and short-term reversal profits. Journal of Banking and Finance. 36, 371-382.

Grossman, S., Miller. M. H., 1988. Liquidity and Market Structure. Journal of Finance. 43, 617-633.

Hameed, A., Kang, W., Viswanathan, S., 2010. Stock Market Declines and Liquidity. Journal of Finance. 65, 257-293.

Hameed, A., Mian. G. M., 2015. Industries and Stock Return Reversals. Journal of Financial and Quantitative Analysis. 50, 89-117.

Hong, H., Stein, J. C., 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. Journal of finance. 54, 2143-2184.

Hong, H., Lim, T., Stein, J. C., 2000. Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. Journal of Finance. 55, 265-295.

Jegadeesh, N., 1990. Evidence of Predictable Behavior of Security Returns. Journal of Finance. 45, 881-898.

Jegadeesh, N., Titman, S., 1995. Short-horizon Return Reversals and the Bid-ask Spread. Journal of Financial Intermediation. 4, 116-132.

Lehmann, B., 1990. Fads, martingales and market efficiency. Quarterly Journal of Economics. 105, 1-28.

McLean, D., Pontiff, J., 2016. Does academic research destroy return predictability? Journal of Finance. 71, 5-32.

Miller, E. M., 1977. Risk, uncertainty, and divergence of opinion. Journal of Finance. 32, 1151-1168.

Nagel, S., 2012. Evaporating Liquidity. Review of Financial Studies. 25, 2005-2039.

Newey, W., West, K., 1987. A Simple Positive-Definite Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. Econometrica. 55, 703–708.

Novy-Marx, R., Velikov, M., 2016. A Taxonomy of Anomalies and Their Trading Costs. Review of Financial Studies. 29, 104-147.

Peng, L., 2005. Learning with information capacity constraints. Journal of Financial and Quantitative Analysis. 40, 307–329.

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

Piotroski, J. D., 2000. Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers. Journal of Accounting Research. 38, 1-41.

Piotroski, J. D., So, E. C., 2012. Identifying Expectation Errors in Value/Glamour Strategies: A Fundamental Analysis Approach. Review of Financial Studies. 25, 2841-2875.

Shumway, T., 1997. The delisting bias in CRSP data. Journal of Finance. 52, 327-340.

Shumway, T., Warther, V., 1999. The Delisting Bias in CRSP's Nasdaq Data and Its Implications for the Size Effect. Journal of Finance. 54, 2361-2379.

Stambaugh, R., Yu, J., Yuan, Y., 2012. The short of it: Investor sentiment and anomalies. Journal of Financial Economics. 104, 288-302.

Stein, J. C., 2009. Sophisticated Investors and Market Efficiency. Journal of Finance. 64, 1517-1548.

Stivers, C. T., Sun, L., 2013. Re-examining Reversals in Monthly Stock Returns: Post-Discovery, Size-based, and Time-Variation Evidence. Working paper, University of Louisville.

Turtle, H. J., Wang, K., 2017. The Value in Fundamental Accounting Information. Journal of Financial Research. 40, 113-140.

Yu, J., Yuan, Y. Investor sentiment and the mean–variance relation. Journal of Financial Economics. 100, 367-381.

Table 1: Hypotheses and Predictions

Under the hypothesis of slow incorporation of information, we show that equation (2) implies adjusted returns ($r_{t+1} - u_t$) is equal to the sum of residual return and past cash flow news shocks. Since FSCORE is positively correlated with past cash flow news and residual return is negatively correlated with past 1-month return, this allows us to predict the signs of the adjusted returns for the four cases listed in the table.

	Predictions		
Portfolios	Residual Return $Residual_{t+1}$	Past Cash Flow News Shocks $\frac{1}{n}\sum_{k=0}^{n-1} CF_{t-k+1}$	Adjusted Return $r_{t+1} - u_t$
Past 1-Month Losers and High FSCORE	positive	positive	positive
Past 1-Month Losers and Low FSCORE	positive	negative	ambiguous
Past 1-Month Winners and High FSCORE	negative	positive	ambiguous
Past 1-Month Winners and Low FSCORE	negative	negative	negative

Table 2: Return Predictability of Quarterly FSCORE

This table presents average monthly raw and market-adjusted returns across quarterly FSCORE portfolios in the holding period of one, three, or six months from April 1984 to December 2015. The calculation of quarterly FSCORE is based on nine financial signals from public quarterly financial statement reports. The value of FSCORE ranges from zero to nine. The market-adjusted returns refer to raw returns minus the contemporaneous CRSP value-weighted market index. Low FSCORE, mid FSCORE, or high FSCORE portfolio includes stocks with FSCORE less than four (0-3), between four and six (4-6), or greater than six (7-9), respectively. Our sample includes common stocks listed on NYSE, AMEX, and NASDAQ. Stocks with price less than $5 at the end of formation periods are excluded. The delisting return adjustment follows the rules in Shumway and Warther (1999). N is the number of total firm observations for each FSCORE portfolio during the sample period, and *t*-statistics are reported in parentheses.

	1 Month		3 Months		6 Months		
FSCORE	Raw	Market-adjusted	Raw	Market-adjusted	Raw	Market-adjusted	N
0	-0.29	-1.16	-0.02	-0.94	-0.02	-0.98	1,342
1	-0.37	-1.31	-0.07	-1.01	0.14	-0.81	10,592
2	0.16	-0.78	0.28	-0.66	0.37	-0.57	36,954
3	0.52	-0.42	0.56	-0.38	0.58	-0.37	79,784
4	0.75	-0.19	0.79	-0.16	0.81	-0.13	139,016
5	1.04	0.09	1.02	0.08	1.02	0.07	168,754
6	1.27	0.33	1.25	0.31	1.21	0.27	157,519
7	1.52	0.58	1.48	0.54	1.41	0.47	119,391
8	1.55	0.61	1.48	0.54	1.46	0.52	52,369
9	1.68	0.74	1.64	0.69	1.58	0.64	8450
Low FSCORE (0-3)	0.33	-0.61	0.42	-0.52	0.48	-0.47	128,672
	(0.99)	(-3.40)	(1.26)	(-2.95)	(1.42)	(-2.62)	
Mid FSCORE (4-6)	1.04	0.09	1.03	0.09	1.02	0.08	465,289
	(3.66)	(0.76)	(3.64)	(0.72)	(3.60)	(0.64)	
High FSCORE (7-9)	1.54	0.59	1.49	0.54	1.44	0.49	180,210
	(5.91)	(5.25)	(5.71)	(4.90)	(5.49)	(4.51)	
High - Low	1.20	1.20	1.07	1.07	0.96	0.96	
(t-statistic)	(8.84)	(8.84)	(8.14)	(8.14)	(7.42)	(7.42)	

Table 3: Returns to Short-Term Reversal Strategies Conditional on Fundamental Strength

Panel A presents average monthly raw returns and risk-adjusted returns of equal-weighted portfolios independently sorted on past 1-month returns and firms' most recently available quarterly FSCORE. FF3 refers to Fama-French 3-factor adjusted returns. FF3MR augments FF3 with momentum and short-term reversal factor. FF5 refers to Fama-French 5-factor model. Each month, stocks are independently sorted into five portfolios based on their past 1-month returns, and three portfolios based on their quarterly FSCORE. The interaction of reversal portfolios and FSCORE portfolios produce 15 portfolios. The fundamental-anchored reversal (FAR) portfolio buys past 1-month (1M) losers with high FSCORE and shorts past 1-month (1M) winners with low FSCORE. The fundamental-unanchored reversal (FUR) portfolio buys 1M losers with low FSCORE and shorts 1M winners with high FSCORE. Simple reversal refers to the simple short-term reversal strategy that buys bottom quintile of 1M losers and shorts top quintile of 1M winners. Low FSCORE, mid FSCORE, or high FSCORE portfolio includes stocks with FSCORE less than four, between four and six, or greater than six, respectively. Our sample includes common stocks listed on NYSE, AMEX, and NASDAQ. Stocks with price less than $5 at the end of formation periods are excluded. Panel B reports the industry-adjusted returns for these portfolios. Following Fama and French (1997), we classify firms into 17 industries based on their 4-digit standard industrial classification (SIC) codes. We rank stocks into five groups based on their past 1-month returns within each industry each month, then we assign all stocks into five portfolios based on their ranks. The sample period is from April 1984 to December 2015. Newey and West (1987) adjusted *t*-statistics are reported in parentheses.

Panel A

	Raw Return				FF3				FF3MR	FF5
FSCORE	Low	Mid	High	H-L	Low	Mid	High	H-L	H-L	H-L
Loser	0.50	1.30	1.89	1.39	-0.72	0.14	0.72	1.43	1.27	1.04
	(1.20)	(3.83)	(5.54)	(5.66)	(-4.21)	(1.13)	(4.23)	(6.94)	(6.06)	(5.63)
2	0.46	1.17	1.56	1.10	-0.63	0.10	0.51	1.14	1.08	0.92
	(1.36)	(4.09)	(5.77)	(6.40)	(-4.69)	(1.18)	(4.58)	(8.01)	(7.15)	(6.13)
3	0.32	1.12	1.58	1.27	-0.74	0.11	0.62	1.36	1.25	1.13
	(0.95)	(4.26)	(6.35)	(7.50)	(-6.75)	(1.59)	(6.00)	(9.56)	(8.60)	(8.39)
4	0.34	0.88	1.40	1.06	-0.65	-0.09	0.44	1.09	0.98	0.83
	(1.05)	(3.31)	(5.28)	(6.80)	(-5.05)	(-1.33)	(4.60)	(7.56)	(6.44)	(6.12)
Winner	0.07	0.70	1.26	1.20	-0.92	-0.27	0.32	1.24	1.08	0.88
	(0.17)	(2.11)	(3.91)	(7.53)	(-4.92)	(-2.31)	(2.40)	(8.04)	(7.17)	(5.95)
L-W	0.43	0.60	0.62		0.20	0.42	0.40			
	(1.70)	(3.11)	(2.63)		(0.73)	(1.94)	(1.65)			
Fundamental-anchored Reversal				1.82				1.64	1.42	1.31
				(6.03)				(5.42)	(6.59)	(4.28)
Fundamental-unanchored Reversal				-0.77				-1.03	-0.93	-0.61
				(-3.07)				(-4.18)	(-5.10)	(-1.99)
Simple Reversal (Quintile)				0.50				0.30	0.23	0.36
				(2.56)				(1.37)	(1.94)	(1.32)
FAR - Simple Reversal (mean diff.)				1.32				1.34	1.19	0.95
				(6.86)				(8.27)	(7.24)	(6.25)

Table 3: (continued)

Panel B

	Raw Return				FF3				FF3MR	FF5
FSCORE	Low	Mid	High	H-L	Low	Mid	High	H-L	H-L	H-L
Loser	0.56	1.37	2.00	1.45	-0.65	0.23	0.83	1.48	1.33	1.08
	(1.37)	(4.14)	(5.91)	(5.68)	(-3.87)	(1.88)	(4.90)	(6.75)	(6.17)	(5.60)
2	0.54	1.17	1.58	1.05	-0.56	0.1	0.54	1.1	1.02	0.86
	(1.57)	(4.04)	(5.76)	(5.62)	(-3.91)	(1.28)	(5.06)	(6.93)	(6.05)	(4.97)
3	0.30	1.07	1.60	1.30	-0.74	0.07	0.64	1.38	1.25	1.12
	(0.89)	(4.08)	(6.42)	(6.90)	(-6.58)	(1.06)	(6.64)	(8.51)	(7.56)	(7.88)
4	0.18	0.90	1.31	1.13	-0.83	-0.08	0.33	1.17	1.06	0.90
	(0.54)	(3.34)	(5.05)	(7.47)	(-6.76)	(-1.22)	(3.90)	(8.08)	(6.70)	(6.31)
Winner	0.06	0.66	1.23	1.18	-0.93	-0.32	0.29	1.22	1.05	0.86
	(0.14)	(2.05)	(3.96)	(6.79)	(-5.02)	(-2.97)	(2.47)	(7.59)	(6.69)	(5.75)
L-W	0.50	0.71	0.77		0.28	0.55	0.54			
	(1.99)	(3.98)	(3.59)		(1.05)	(2.79)	(2.50)			
Fundamental-anchored Industry Reversal				1.94				1.77	1.58	1.41
				(6.58)				(6.01)	(7.23)	(4.95)
Fundamental-unanchored Industry Reversal				-0.68				-0.94	-0.80	-0.53
				(-2.80)				(-4.06)	(-4.41)	(-1.94)
Simple Industry Reversal (Quintile)				0.61				0.43	0.39	0.47
				(3.47)				(2.18)	(3.56)	(2.01)
FAR - Simple Reversal (mean diff.)				1.34				1.34	1.20	0.94
				(6.79)				(8.03)	(7.29)	(6.09)

Table 4: Regression Analysis of Fundamental-Based Short-Term Return Reversals

This table presents average estimated coefficients from monthly cross-sectional regressions from April 1984 to December 2015. The dependent variable, $R_{i\ t+1}$, is a stock's one-month-ahead raw return. The indicator variable Winner, Middle, or Loser is equal to one if the stock's past 1-month return is above the 80th percentile, between 20th and 80th percentile, or 80th percentile of all stocks' returns each month, respectively, zero otherwise. The indicator LowFSCORE, MidFSCORE, or HighFSCORE is equal to one if the stock's FSCORE is less than four (0-3), between four and six (4-6), greater than six (7-9), respectively. Size is the stock's market capitalization at the end of formation month t, BM is the book-to-market ratio at the end of prior year, Momentum is the past 6-month cumulative return from t-6 to t-1, Volatility is the stock's monthly return volatility, Illiquidity measures stock illiquidity defined in Amihud (2002), and Turnover is defined as the trading volume divided by the number of shares outstanding in the formation month t. Each month, Size, BM, Momentum, Volatility, Illiquidity, and Turnover are assigned to deciles (with a score ranging from one to ten). Following Piotroski and So (2012), the intercept is suppressed in the regression to avoid collinearity. N is the number of stock observations in the sample. Newey and West (1987) adjusted *t*-statistics are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
Winner	0.7083	1.2529	1.278	1.4491	0.0514
	(2.28)	(4.21)	(4.14)	(3.23)	(0.13)
Winner*LowFSCORE		-1.2069	-1.2077	-1.0095	-1.0179
		(-6.63)	(-6.67)	(-6.39)	(-6.50)
Winner*MidFSCORE		-0.5754	-0.5844	-0.5108	-0.5114
		(-5.34)	(-5.42)	(-5.13)	(-5.13)
Middle	1.07	1.0702	1.1042	1.3105	-0.042
	(4.15)	(4.14)	(3.95)	(2.82)	(-0.11)
Middle*LowFSCORE		-0.6834	-0.68	-0.584	-0.5962
		(-7.95)	(-8.03)	(-8.02)	(-8.27)
Middle*HighFSCORE		0.4409	0.4371	0.3785	0.3825
		(7.62)	(7.58)	(7.72)	(7.86)
Loser	1.3212	0.623	0.6161	1.0777	-0.2912
	(3.68)	(1.51)	(1.45)	(2.00)	(-0.64)
Loser*MidFSCORE		0.7374	0.7448	0.6744	0.6729
		(5.09)	(5.14)	(4.97)	(4.95)
Loser*HighFSCORE		1.325	1.3337	1.1644	1.1703
		(6.71)	(6.81)	(6.78)	(6.79)
Size			-0.0044	-0.0873	-0.0265
			(-0.23)	(-2.63)	(-0.83)
BM				0.0478	0.0465
				(2.85)	(2.74)
Momentum				0.1258	0.1253
				(5.07)	(5.09)
Volatility				-0.0671	-0.10
				(-2.29)	(-4.29)
Illiquidity				-0.0695	0.058
				(-1.99)	(1.68)
Turnover					0.0946
					(3.73)
Simple Reversal	0.61				
	(2.82)				
Fundamental-anchored Reversal		1.90	1.88	1.80	1.85
		(7.04)	(6.99)	(7.92)	(8.13)
Fundamental-unanchored Reversal		-0.63	-0.66	-0.37	-0.34
		(-2.24)	(-2.38)	(-1.66)	(-1.53)
Adj. R^2	0.129	0.132	0.137	0.160	0.162
N	665,229	665,229	665,229	665,229	665,229

Table 5: Short-Term Reversal Portfolios Sorted on Fundamental Strength, Cash Flow News, and Past Returns

The table reports the average monthly returns of equal-weighted short-term reversal portfolios sorted on terciles of fundamental strength (FSCORE), cash flow news, and past 1-month return. Panel A uses analyst forecast revision (FREV) as a simple proxy for cash flow news. Panel B uses a more complex cash flow new proxy (CF) proposed by Da, Liu, and Schaumburg (2014). Identified with a square bracket in the table, portfolio A (C) consists of firms that are past 1-month losers with strong cash flow news and low (high) FSCOREs. Portfolio B (D) consists of firms that are past 1-month winners with weak cash flow news and low (high) FSCOREs. Portfolio (A-B) denotes the portfolio strategy that is long portfolio A and short portfolio B. Portfolios (C-D), (C-B), and (A-D) are similarly defined. The sample period is from April 1984 to December 2015. Newey and West (1987) adjusted *t*-statistics are reported in parentheses.

Panel A: Simple Measure of Cash Flow News

	Low FSCORE Firms				High FSCORE Firms			
	1M loser	2	1M winner	LMW	1M loser	2	1M winner	LMW
FREV1	0.45	0.28	-0.37 [B]	0.82	1.61	1.08	0.26 [D]	1.35
	(1.06)	(0.69)	(-0.87)	(2.99)	(4.23)	(3.63)	(0.81)	(5.28)
FREV2	0.49	0.49	0.00	0.49	1.65	1.37	1.01	0.63
	(1.26)	(1.38)	(0.01)	(1.91)	(5.16)	(5.13)	(3.37)	(3.04)
FREV3	0.84 [A]	0.58	0.84	0.00	1.88 [C]	1.86	1.79	0.09
	(1.80)	(1.52)	(2.14)	(0.00)	(5.38)	(6.30)	(5.24)	(0.35)
FREV3-FREV1	0.39	0.29	1.20		0.29	0.80	1.53	
	(1.27)	(0.92)	(3.81)		(1.29)	(4.44)	(7.59)	
Portfolio (A-B)	1.20							
	(3.52)							
portfolio (C-D)	1.64							
	(6.18)							
Portfolio (C-B)	2.27							
	(6.35)							
Portfolio (A-D)	0.58							
	(1.87)							

Table 5: (continued)

Panel B: Complicated Measure of Cash Flow News

	Low FSCORE Firms				High FSCORE Firms			
	1-M loser	2	1-M winner	LMW	1-M loser	2	1-M winner	LMW
CF1	0.59	0.53	-0.04 [B]	0.63	1.75	1.27	0.69 [D]	1.05
	(1.33)	(1.41)	(-0.10)	(2.08)	(4.93)	(4.43)	(2.16)	(4.17)
CF2	0.61	0.34	-0.21	0.81	1.61	1.25	0.70	0.91
	(1.50)	(0.96)	(-0.63)	(2.91)	(4.54)	(4.55)	(2.34)	(3.29)
CF3.	0.91 [A]	0.69	0.70	0.21	1.74 [C]	1.62	1.49	0.26
	(2.05)	(2.02)	(1.99)	(0.63)	(5.36)	(6.11)	(4.74)	(1.06)
CF3-CF1	0.32	0.16	0.74		-0.01	0.35	0.79	
	(1.05)	(0.64)	(2.38)		(-0.03)	(2.14)	(4.42)	
Portfolio (A-B)	0.95							
	(2.73)							
portfolio (C-D)	1.05							
	(4.28)							
Portfolio (C-B)	1.78							
	(5.21)							
Portfolio (A-D)	0.22							
	(0.78)							

Table 6: Robustness Tests

This table reports the average monthly raw and risk-adjusted returns for the simple, fundamental-anchored, and fundamental-unanchored reversal strategies in the non-January sample, two subperiods, an alternative classification of fundamental strength, annual FSCORE, a sample where we skip 1-day between the formation and holding months, and a sample where we use the report date of quarterly earnings (RDQ) to identify the real-time fundamental information. Results for panels A to F are based on equal-weighted portfolios. Panels G and H report results based on gross-return weighted portfolios as well as value-weighted portfolio after adjustments for industry effect. Newey and West (1987) adjusted *t*-statistics are in parentheses.

	Raw Return	FF3	FF5	FF3MR
	Panel A: Non-January			
Simple Reversal	0.25	0.02	0.00	0.18
	(1.26)	(0.09)	(0.01)	(1.54)
Fundamental-anchored Reversal	1.64	1.40	0.95	1.37
	(5.35)	(4.43)	(2.75)	(7.09)
Fundamental-unanchored Reversal	1.05	-1.33	-0.92	-0.96
	(-3.86)	(-4.76)	(-2.62)	(-4.94)
FAR - Simple Reversal	1.38	1.38	0.95	1.19
	(6.40)	(8.03)	(6.07)	(7.07)
	Panel B: Subperiods			
	1984-1999			
Simple Reversal	0.52	0.35	0.23	0.32
	(2.00)	(1.36)	(0.75)	(2.74)
Fundamental-anchored Reversal	2.29	2.11	1.88	1.99
	(6.72)	(6.32)	(5.10)	(9.55)
Fundamental-unanchored Reversal	-1.02	-1.23	-1.14	-1.15
	(-2.91)	(-3.80)	(-2.80)	(-4.46)
FAR - Simple Reversal	1.77	1.76	1.65	1.67
	(9.65)	(9.99)	(10.09)	(10.46)
	2000-2015			
Simple Reversal	0.48	0.44	0.42	0.27
	(1.84)	(1.58)	(1.33)	(1.55)
Fundamental-anchored Reversal	1.35	1.38	0.83	1.12
	(3.10)	(3.37)	(2.18)	(3.56)
Fundamental-unanchored Reversal	-0.52	-0.63	-0.20	-0.71
	(-1.51)	(-2.18)	(-0.55)	(-3.24)
FAR - Simple Reversal	0.87	0.93	0.41	0.86
	(1.84)	(4.22)	(2.03)	(3.68)

Table 6 (continued)

	Raw Return	FF3	FF5	FF3MR
	Panel C: Alternative Low/High FSCORE			
	Low FSCORE (0-2) & High FSCORE (8-9)			
Fundamental-anchored Reversal	2.05	1.82	1.39	1.58
	(5.39)	(4.55)	(3.49)	(-4.56)
Fundamental-unanchored Reversal	-1.08	-1.35	-0.93	-1.21
	(-3.31)	(-4.41)	(-2.69)	(-4.97)
FAR - Simple Reversal	1.55	1.51	1.04	1.35
	(5.27)	(5.27)	(3.74)	(4.71)
	Low FSCORE (0-4) & High FSCORE (6-9)			
Fundamental-anchored Reversal	1.55	1.36	1.15	1.19
	(5.97)	(5.05)	(4.07)	(6.51)
Fundamental-unanchored Reversal	-0.47	-0.69	-0.40	-0.65
	(-2.22)	(-3.18)	(-1.44)	(-4.42)
FAR - Simple Reversal	1.04	1.06	0.80	0.96
	(7.65)	(9.37)	(8.44)	(8.01)
	Panel D: Annual FSCORE			
Simple Reversal	0.57	0.34	0.36	0.30
	(2.95)	(1.65)	(1.65)	(2.47)
Fundamental-anchored Reversal	1.31	1.21	1.01	1.06
	(4.24)	(3.73)	(2.97)	(4.29)
Fundamental-unanchored Reversal	-0.10	-0.43	-0.20	-0.42
	(-0.45)	(-2.07)	(-0.75)	(-2.64)
FAR - Simple Reversal	0.74	0.86	0.63	0.77
	(3.60)	(4.75)	(3.75)	(4.24)
	Panel E: Skip 1-Day			
Simple Reversal	0.19	-0.01	0.05	-0.05
	(1.02)	(-0.04)	(0.21)	(-0.36)
Fundamental-anchored Reversal	1.35	1.17	0.87	0.99
	(5.04)	(4.21)	(3.17)	(4.80)
Fundamental-unanchored Reversal	-0.90	-1.17	-0.76	-1.04
	(-3.65)	(-4.82)	(-2.48)	(-5.29)
FAR - Simple Reversal	1.16	1.18	0.82	1.04
	(6.42)	(7.80)	(5.36)	(6.75)

Table 6 (continued)

	Raw Return	FF3	FF5	FF3MR
	Panel F: RDQ			
Simple Reversal	0.49	0.30	0.38	0.22
	(2.63)	(1.38)	(1.41)	(1.77)
Fundamental-anchored Reversal	1.90	1.70	1.44	1.45
	(6.25)	(5.49)	(4.51)	(6.29)
Fundamental-unanchored Reversal	-0.71	-0.92	-0.59	-0.86
	(-3.13)	(-3.92)	(-1.89)	(-4.79)
FAR - Simple Reversal	1.41	1.40	1.07	1.23
	(6.92)	(8.04)	(6.19)	(6.66)
	Panel G: Gross-Return Weighted Portfolios			
Simple Reversal	0.52	0.32	0.35	0.24
	(2.60)	(1.44)	(1.29)	(1.95)
Fundamental-anchored Reversal	1.86	1.68	1.32	1.45
	(6.03)	(5.47)	(4.26)	(6.47)
Fundamental-unanchored Reversal	-0.77	-1.03	-0.62	-0.93
	(-3.05)	(-4.11)	(-1.99)	(-5.05)
FAR - Simple Reversal	1.34	1.36	0.97	1.21
	(6.96)	(8.31)	(6.35)	(7.25)
	Panel H: Industry-adjusted Value-Weighted Portfolios			
Simple Reversal	0.34	0.16	0.14	0.07
	(1.79)	(0.82)	(0.64)	(0.65)
Fundamental-anchored Reversal	0.92	0.74	0.49	0.52
	(2.91)	(2.47)	(1.46)	(2.06)
Fundamental-unanchored Reversal	-0.47	-0.75	-0.52	-0.72
	(-1.54)	(-2.52)	(-1.55)	(-3.08)
FAR - Simple Reversal	0.58	0.58	0.35	0.45
	(2.31)	(2.48)	(1.42)	(1.93)

Table 7: Fundamental-Based Return Reversals Conditional on Stock Characteristics

This table presents average monthly raw and risk-adjusted returns for fundamental-based reversal strategies conditional on different stock characteristics. Panel A reports returns to fundamental-anchored (-unanchored) reversal strategies within subsamples of large stocks and small stocks, respectively. Small (large) stocks are those in the bottom (top) 40% of all sample stocks in term of market capitalization at the end of formation month t. Panel B reports the results for subsamples of high and low volatile stocks. High (low) volatile stocks are those in the top (bottom) 40% of all sample stocks in term of monthly return volatility in month t. Panel C reports the results for subsamples of liquid and illiquid stocks. We use the Amihud (2002) illiquidity measure to measure the stock's illiquidity. Liquid (illiquid) stocks are those in the bottom (top) 40% of all sample stocks in term of Amihud illiquidity measure in month t. Panel D reports the results for subsamples of high and low turnover stocks. High (low) turnover stocks are those in the top (bottom) 40% of all sample stocks in term of monthly stock turnover in month t. The sample period is from April 1984 to December 2015. Newey and West (1987) adjusted *t*-statistics are shown in parentheses.

	Raw	FF3	FF5	FF3MR	Raw	FF3	FF5	FF3MR
Panel A: Size	Large Stocks				Small Stocks			
Fundamental-anchored Reversal	0.95	0.75	0.49	0.53	2.42	2.27	1.95	2.15
	(3.06)	(2.48)	(1.58)	(2.41)	(6.82)	(5.78)	(4.76)	(6.54)
Fundamental-unanchored Reversal	-0.76	-1.07	-0.75	-1.06	-0.99	-1.27	-0.83	-1.12
	(-2.69)	(-3.75)	(-2.19)	(-4.92)	(-3.09)	(-4.13)	(-2.49)	(-3.83)
Panel B: Return Volatility	High Volatile Stocks				Low Volatile Stocks			
Fundamental-anchored Reversal	2.16	1.94	1.52	1.78	1.41	1.31	1.17	1.26
	(5.35)	(4.61)	(3.57)	(5.43)	(7.52)	(6.91)	(6.32)	(7.11)
Fundamental-unanchored Reversal	-1.28	-1.60	-1.16	-1.39	0.14	-0.03	0.15	0.07
	(-3.32)	(-4.19)	(-2.70)	(-4.33)	(0.71)	(-0.15)	(0.73)	(0.39)
Panel C: Illiquidity	Illiquid Stocks				Liquid Stocks			
Fundamental-anchored Reversal	2.62	2.50	2.22	2.36	1.11	0.87	0.56	0.69
	(7.55)	(6.69)	(5.69)	(7.40)	(3.31)	(2.61)	(1.62)	(2.94)
Fundamental-unanchored Reversal	-0.83	-1.11	-0.72	-0.99	-1.07	-1.37	-1.03	-1.29
	(-2.85)	(-4.02)	(-2.59)	(-3.73)	(-3.24)	(-4.03)	(-2.41)	(-5.19)
Panel D: Turnover	High Turnover Stocks				Low Turnover Stocks			
Fundamental-anchored Reversal	1.09	0.84	0.45	0.59	2.57	2.48	2.26	2.43
	(2.60)	(1.94)	(1.01)	(1.97)	(10.61)	(9.84)	(9.40)	(9.80)
Fundamental-unanchored Reversal	-1.35	-1.62	-1.22	-1.43	-0.58	-0.82	-0.44	-0.69
	(-3.53)	(-4.13)	(-2.58)	(-4.42)	(-2.20)	(-3.29)	(-1.82)	(-2.94)

Table 8: Short-Term Return Reversals and Fundamental Information Announcements

This table presents average monthly raw and risk-adjusted returns for simple and fundamental-based reversal strategies within subsamples of RDQ and non-RDQ. The RDQ subsample includes stock observations where their Report Date of Quarterly Earnings (RDQ) are in the formation month of reversals. The non-RDQ subsample includes stock observations where there is no quarterly earnings announcement in the reversal formation month. The definitions of simple, industry-based and fundamental-based reversal strategies are the same in previous tables. The sample period is from April 1984 to December 2015. Newey and West (1987) adjusted *t*-statistics are reported in parentheses.

	Non-RDQ				RDQ			
	Raw	FF3	FF5	FF3MR	Raw	FF3	FF5	FF3MR
Simple Reversal (Quintile)	0.83	0.60	0.67	0.54	-0.19	-0.33	-0.31	-0.44
	(3.79)	(2.41)	(2.17)	(3.98)	(-0.96)	(-1.63)	(-1.38)	(-2.96)
Simple Reversal (Decile)	1.07	0.78	0.86	0.74	-0.32	-0.45	-0.39	-0.55
	(3.83)	(2.48)	(2.24)	(4.04)	(-1.18)	(-1.54)	(-1.20)	(-2.35)
Industry-based Reversal (Quintile)	0.98	0.76	0.82	0.73	-0.03	-0.16	-0.15	-0.22
	(4.87)	(3.37)	(2.99)	(5.70)	(-0.16)	(-0.80)	(-0.72)	(-1.47)
Fundamental-anchored Reversal	2.28	2.07	1.72	1.86	1.04	1.02	0.78	0.83
	(6.56)	(5.74)	(4.71)	(7.18)	(2.64)	(2.93)	(2.32)	(2.37)
Fundamental-unanchored Reversal	-0.51	-0.77	-0.32	-0.70	-1.35	-1.55	-1.29	-1.46
	(-1.88)	(-2.85)	(-0.92)	(-3.26)	(-3.80)	(-4.58)	(-3.59)	(-4.15)
Fundamental-anchored Industry Reversal	2.38	2.16	1.79	1.97	1.12	1.08	0.80	0.94
	(7.06)	(6.37)	(5.49)	(7.71)	(3.05)	(3.26)	(2.70)	(2.96)
Fundamental-unanchored Industry Reversal	-0.36	-0.62	-0.22	-0.53	-1.33	-1.52	-1.15	-1.41
	(-1.42)	(-2.52)	(-0.70)	(-2.67)	(-3.82)	(-4.62)	(-3.57)	(-4.24)

Table 9: Liquidity, Sentiment, and Short-Term Reversals: Time Series Regressions

This table presents average coefficients for the following predictive regressions:

$$R_{i\,t} = a + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 X_{t-1} + \varepsilon_t$$

The dependent variable is either the reversal portfolio (long-short) returns or the excess returns from the long or short legs of the reversal portfolios. The independent variables include Fama-French 3 factors (coefficients on these factors are not reported to conserve space) and a lagged proxy for either liquidity or investor sentiment (X), including: the DOWN market dummy, realized market volatility, market illiquidity, CBOE's implied volatility index (VIX), Baker and Wurgler (2006) aggregate sentiment index (BW), or the number of net share issuance (S). The DOWN market dummy takes a value of 1 if the past 3-month CRSP value-weighted market index is negative, and 0 otherwise. The realized market volatility is calculated as the standard deviation of realized market index in the formation month. The market illiquidity measure is computed using the average of detrended Ahmihud (2002) illiquidity measure. The aggregate sentiment index and net share issuance are from Baker and Wurgler (2006). The sample period is from April 1984 to December 2015 except for investor sentiment which ends in September 2015. Newey and West (1987) adjusted *t*-statistics are reported in parentheses.

Panel A: Simple Short-Term Reversal

	Long-Short	Long (1M Losers)	Short (1M Winners)	Long-Short	Long (1M Losers)	Short (1M Winners)
	Full Sample			**Non-RDQ Sample**		
DOWN	**0.0209**	**0.0101**	**-0.0108**	**0.0238**	**0.0103**	**-0.0136**
	(3.24)	(2.76)	(-2.77)	(3.58)	(2.46)	(-3.72)
Market Volatility	**1.2154**	**0.8256**	-0.3898	**1.2821**	**0.8974**	-0.3847
	(2.11)	(2.16)	(-1.33)	(2.15)	(1.98)	(-1.40)
Market Illiquidity	**0.1816**	**0.085**	**-0.0966**	**0.1849**	**0.0793**	**-0.1057**
	(2.75)	(2.60)	(-2.30)	(2.85)	(2.23)	(-2.57)
VIX	**0.0011**	**0.0006**	**-0.0005**	**0.0013**	**0.0007**	**-0.0005**
	(2.58)	(2.66)	(-1.77)	(2.68)	(2.48)	(-2.06)
BW Sentiment	**0.0087**	0.003	**-0.0058**	0.007	0.0024	**-0.0046**
	(1.65)	(0.80)	(-2.41)	(1.14)	(0.48)	(-1.92)
S	**0.07**	0.0025	**-0.0067**	0.0517	-0.0102	**-0.0619**
	(2.08)	(0.12)	(-3.06)	(1.35)	(-0.42)	(-2.65)

Panel B: Fundamental-anchored Reversal

	Long-Short	Long (1M Losers)	Short (1M Winners)	Long-Short	Long (1M Losers)	Short (1M Winners)
		Full Sample			**Non-RDQ Sample**	
DOWN	**0.0154**	0.0045	**-0.0109**	**0.0151**	0.0043	**-0.0109**
	(2.48)	(1.19)	(-2.83)	(2.18)	(0.88)	(-2.66)
Market Volatility	0.6802	0.4328	-0.2474	0.4059	0.275	-0.1309
	(1.00)	(1.00)	(-0.69)	(0.53)	(0.47)	(-0.33)
Market Illiquidity	0.1084	0.0406	-0.0678	0.065	0.0088	-0.562
	(1.57)	(1.01)	(-1.61)	(0.84)	(0.19)	(-1.13)
VIX	0.0009	0.0005	-0.0004	0.0008	0.0004	-0.0004
	(1.55)	(1.55)	(-1.28)	(1.22)	(1.08)	(-1.02)
BW Sentiment	**0.0138**	**0.0091**	**-0.0048**	**0.0132**	**0.0094**	-0.0038
	(3.25)	(3.39)	(-1.87)	(2.56)	(2.46)	(-1.26)
S	**0.0882**	0.0201	**-0.0681**	0.0767	-0.0062	**-0.0828**
	(2.19)	(0.82)	(-2.51)	(1.52)	(-0.20)	(-2.58)

Table 10: Time Series Regressions: Subsamples

The dependent variable is the excess return of long or short leg of the fundamental-anchored reversal (FAR) portfolios within each subsample. The subsamples include top and bottom 30% stocks sorted by size, book-market ratio, Amihud illiquidity measure, and idiosyncratic volatility. The explanatory variables include Fama-French 3-factors (market, size, and book-to-market ratio) and lagged values of DOWN market dummy, realized market volatility, market illiquidity, CBOE's implied volatility index (VIX), Baker and Wurgler (2006) aggregate sentiment index (BW), and the number of net share issuance (S). The DOWN market dummy takes a value of 1 if the past 3-month CRSP value-weighted market index is negative, and 0 otherwise. The realized market volatility is calculated as the standard deviation of realized market index in the formation month. The market illiquidity measure is computed using the average of detrended Ahmihud (2002) illiquidity measure. The aggregate sentiment index and net share issuance are from Baker and Wurgler (2006). The sample period is from April 1984 to December 2015 except for the sentiment index which ends in September 2015. Newey and West (1987) adjusted *t*-statistics are reported in parentheses.

	FAR Portfolio Long Leg Excess Return (1M Losers)						FAR Portfolio Short Leg Excess Return (1M Winners)					
	DOWN	MKT Volatility	MKT Illiquidity	VIX	BW	S	DOWN	MKT Volatility	MKT Illiquidity	VIX	BW	S
Small	0.0043	0.4607	0.0342	**0.0006**	**0.0085**	0.0196	**-0.0133**	-0.6142	**-0.1496**	**-0.0008**	-0.0032	**-0.1068**
	(0.99)	(0.93)	(0.83)	(1.75)	(2.22)	(0.56)	(-2.86)	(-1.43)	(-2.87)	(-2.10)	(-0.93)	(-2.78)
Large	0.0026	0.3575	0.0579	0.0003	**0.0073**	0.0127	-0.0032	**-0.4141**	0.0364	0.0001	**-0.0065**	-0.0391
	(0.60)	(0.88)	(1.30)	(1.12)	(2.57)	(0.49)	(-0.67)	(-3.28)	(0.73)	(0.18)	(-2.44)	(-1.24)
Value	0.0048	0.277	**0.0656**	0.0004	**0.0112**	0.0453	**-0.0078**	0.1695	-0.0585	0	0.0014	-0.0459
	(1.12)	(0.66)	(1.68)	(1.25)	(4.22)	(1.49)	(-2.07)	(0.43)	(-1.23)	(-0.07)	(0.46)	(-1.39)
Growth	0.0051	0.4627	0.0402	0.0005	**0.0101**	0.0085	**-0.012**	-0.441	-0.0451	-0.0005	**-0.0092**	**-0.0859**
	(1.18)	(0.92)	(0.84)	(1.39)	(2.74)	(0.31)	(-2.49)	(-1.03)	(-0.94)	(-1.29)	(-2.47)	(-2.43)
Illiquid	0.0017	0.1987	0.0329	0.0004	**0.0063**	0.0404	**-0.0136**	-0.5373	**-0.1456**	**-0.0007**	-0.0057	**-0.1031**
	(0.45)	(0.49)	(0.86)	(1.43)	(2.03)	(1.29)	(-2.78)	(-1.25)	(-2.80)	(-1.75)	(-1.60)	(-2.61)
Liquid	0.0045	0.5611	0.0581	0.0004	**0.0099**	-0.0135	-0.0026	0.4562	0.0223	0.0001	-0.0038	-0.0406
	(0.91)	(1.16)	(1.15)	(1.22)	(2.54)	(-0.43)	(-0.54)	(0.91)	(0.41)	(0.13)	(-1.24)	(-1.13)
High IVOL	0.0071	0.6199	0.0346	0.0005	**0.0121**	0.0012	**-0.013**	-0.4622	-0.1128	-0.0005	**-0.0076**	**-0.1077**
	(1.40)	(1.06)	(0.70)	(1.22)	(2.92)	(0.04)	(-2.41)	(-0.94)	(-1.86)	(-1.17)	(-2.15)	(-3.14)
Low IVOL	0.0008	0.3386	0.0354	0.0003	**0.0052**	0.0286	**-0.0086**	**-0.4848**	0.0112	**-0.0007**	-0.0004	-0.0113
	(0.26)	(1.23)	(0.98)	(1.33)	(3.03)	(1.34)	(-3.20)	(-2.09)	(0.47)	(-3.95)	(-0.16)	(-0.48)

Table 11: Transaction Costs and Sharpe Ratios

This table presents portfolio turnover ratios, transaction costs, monthly raw returns, monthly standard deviation, and Sharpe ratios for simple and fundamental-based reversal strategies. Portfolio turnover (%) measures the percentage of stocks that are not in the same portfolio in two consecutive months. The half effective spread (%) is the absolute value of the difference between the transaction price and bid-ask midpoint scaled by transaction price ($|(P-P_{Mid})/P|$). Transaction cost is the sum of the long and the short leg of half effective spread times portfolio turnover ratio. Sharpe ratio is the annualized Sharpe ratio. Net return (in percentage) is the difference between raw return and transaction cost. The sample period is from April 1984 to December 2015. The numbers in this table are in percentage.

	Portfolio Turnover	Effective Spread	Transaction Cost	Raw Return	Monthly Std.	Sharpe Ratio	Net Return
Simple Reversal (Quintile)	78.91	0.705	1.04	0.50	4.37	0.40	-0.54
	80.96	0.600					
Simple Reversal (Decile)	87.28	0.760	1.23	0.58	5.49	0.36	-0.65
	88.76	0.642					
Industry-based Reversal (Quintile)	79.65	0.705	1.05	0.62	3.90	0.55	-0.43
	81.45	0.600					
Fundamental-anchored Reversal	86.34	0.687	1.16	1.82	5.40	1.17	0.66
	85.75	0.664					
Fundamental-anchored Industry Reversal	86.74	0.685	1.17	1.94	5.19	1.30	0.77
	86.15	0.663					
Fundamental-anchored Reversal	91.03	0.698	1.26	2.28	6.07	1.30	1.02
(Non-RDQ)	90.56	0.692					
Fundamental-anchored Industry Reversal	91.43	0.696	1.27	2.38	5.79	1.43	1.11
(Non-RDQ)	90.95	0.693					

Table 12: Returns to Fundamental-Anchored Reversal Strategies in Event Time

This table presents raw returns to fundamental-anchored reversal strategies in event time. The sample period is from April 1984 to December 2015. Newey and West (1987) adjusted *t*-statistics are in parentheses.

	First Month	Second Month	Third Month	Fourth Month	Fifth Month
Fundamental-anchored Reversal	1.82	1.03	0.57	0.81	0.62
	(6.03)	(3.66)	(2.42)	(3.74)	(3.07)
Fundamental-anchored Industry Reversal	1.94	1.05	0.64	0.78	0.51
	(6.58)	(3.97)	(2.85)	(3.72)	(2.60)
Fundamental-anchored Reversal	2.28	1.32	0.69	0.97	0.75
(Non-RDQ)	(6.56)	(4.35)	(2.79)	(3.71)	(3.11)
Fundamental-anchored Industry Reversal	2.38	1.41	0.81	0.95	0.64
(Non-RDQ)	(7.06)	(5.09)	(3.17)	(3.77)	(2.65)