Short-Term Return Reversal:

The Long and the Short of It

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ABSTRACT

Stock returns unexplained by "fundamentals", such as cash flow news, are more likely to reverse in the short run than those linked to fundamental news. Making novel use of analyst forecast revisions to measure cash flow news, a simple enhanced reversal strategy generates a risk-adjusted return four times the size of the standard reversal strategy. Importantly, isolating the component of past returns not driven by fundamentals provides a cleaner setting for testing existing theories of short-term reversals. Using this approach, we find that both liquidity shocks and investor sentiment contribute to the observed short-term reversal, but in different ways: Specifically, the reversal profit is attributable to liquidity shocks on the long side as fire sales more likely demand liquidity; and it is attributable to investor sentiment on the short side as short-sale constraints prevent the immediate elimination of overvaluation.

Keywords: Short run reversal , liquidity, sentiment, fundamental news

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I. Introduction

Short-term return reversal in the stock market, a well-established phenomenon for more than 40 years, has been shown to be both robust and of economic significance.[1] Jegadeesh (1990), for example, documents profits of about 2% per month over 1934-1987 using a reversal strategy that buys and sells stocks on the basis of their prior-month returns and holds them for one month. These profits are not readily explainable by direct transaction costs. In an efficient market with a slowly varying stochastic discount factor, asset prices should follow a martingale over short time horizons even though they exhibit predictable variations over longer horizons (see, e.g., Sims (1984)).

Two possible explanations for short-term reversal profits have received much attention in the literature. Shiller (1984), Black (1986), Stiglitz (1989), Summers and Summers (1989), and Subrahmayham (2005), among others, have suggested that short-term reversal profits are evidence that market prices may reflect investor overreaction to information, or fads, or simply cognitive errors. We label this the sentiment-based explanation. Another explanation is based on the price pressure that can occur when the short-term demand curve of a stock is downward sloping and/or the supply curve is upward sloping, as in Grossman and Miller (1988) and Jegadeesh and Titman (1995). In the model of Campbell, Grossman, and Wang (1993), for example, uninformed trades lead to a temporary price concession that, when absorbed by liquidity providers, results in a reversal in price that serves as compensation for those who provide liquidity. Consistent with such a mechanism, Avramov, Chordia and Goyal (2006) find that the standard reversal strategy profits mainly derive from positions in small, high turnover, and illiquid stocks. In fact, Pastor and Stambaugh (2003) suggest directly measuring the degree of illiquidity by the occurrence of an initial price change and subsequent reversal. We label this second explanation the liquidity-based explanation.

These two explanations are not necessarily mutually exclusive. A natural question follows: do liquidity shocks and investor sentiment play different role in driving short-term return reversal? The answer to this question clearly has important bearings on the debate about market efficiency and asset pricing models in general. We attempt to address this question in two steps.

In the first step, we recognize that under both explanations, reversal profits should come from the portion of past return unexplained by the "fundamental" change, which we label as "residual return." We can

[1] See Fama (1965), Jegadeesh (1990) and Lehmann (1990).

think of the "fundamental" component of the stock return to contain three components: (1) the expected return that reflects the rational compensation of risk; (2) cash flow news that is due to changing expectations about fundamental future cash flows; and (3) discount rate news that is due to changing expectations about rational future discount rates. If we can purge these three components out of the realized return to obtain the "residual" return, we can better isolate the non-fundamental return component, be it sentiment-induced mispricing or a price concession triggered by a liquidity shock.[2] Importantly, by focusing on this cleaner source of short-term reversal, we arguably have a superior testing ground for studying alternative explanations of short-term reversal.

Among the three "fundamental" components of stock return, the discount rate news component is probably small at weekly or monthly frequency under the common belief that the stochastic discount factor is slow moving. For this reason, we focus our attention on controlling for the two remaining fundamental components using suitably constructed proxies.

To measure the expected return component, we use the Fama and French (1993) three-factor model, although we stress that the specific choice of model for the expected return is not crucial for studying short-term return reversal since the expected return is small relative to the realized return at high frequency in virtually all commonly used asset pricing models.

A novel feature of our empirical exercise is that we measure the cash flow news component directly using revisions of equity analyst consensus forecasts following the procedures described in Da and Warachka (2009). Similar approaches are used by Easton and Monahan (2005) and Chen, Da and Zhao (2011). Crucially, the use of analyst earnings forecasts allows us to measure cash flow news at monthly frequency in real time, which is necessary for implementing the short-term reversal strategy. Furthermore, computing monthly revisions mitigates analyst forecast biases that persist over this short horizon.

Throughout the paper, we control for industry effects. In other words, all stock returns and their components will effectively be measured in excess of their industry averages. Such industry control has several benefits. First, any residual analyst forecast biases, as long as they are roughly constant across stocks within the same industry, will be alleviated. Second, the industry control also helps to remove any common components in expected returns and discount rate news.

[2]For clarification, since we allow stock price to temporarily deviate from its fundamental value, the three "fundamental" components no longer add up to the realized stock return as in the standard Campbell and Shiller (1988) decomposition framework.

Our key variable of interest, the *residual* return, is computed by subtracting the estimated expected return and cash flow news from the realized return. Notwithstanding the measurement errors associated with our empirical estimates, it is important to note that as long as our estimates are informative about the true expected return and cash flow news, the *residual* return should help to isolate the "true" driver of short-term reversal. Our *residual* return is in spirit similar to the "intangible" return in Daniel and Titman (2006). Daniel and Titman (2006) focuses on long-term return reversal and shows that "intangible" return, or the component of past 5-year-return orthogonal to the firms past accounting performance, predicts future long-run return reversal. In contrast, we focus on short-term return reversal at monthly frequency. Computing *residual* returns over such a short horizon is only made possible by our novel use of analyst forecasts.

By focusing on the *residual* return, we enhance the profitability of the short-term reversal strategy substantially. During our sample period from 1982 to 2009, a *residual-based short-term reversal strategy* that sorts stocks into deciles within each industry on the basis of prior-month residual return generates a monthly alpha of 1.34% with a highly significant t-value of 9.28. Such an alpha is large considering the fact that our sample includes a subset of relatively large and liquid stocks due to the requirement for regular analyst coverage. As a comparison, the standard reversal strategy only generates a monthly alpha of 0.33% with an insignificant t-value of 1.37 in the same sample. The success of the residual-based reversal strategy survives transaction cost analysis and a battery of additional robustness checks.

The enhanced reversal strategy offers a superior testing ground for evaluating different explanations of short-term reversal. In the second step, we obtain fresh insights from separately analyzing the long- and short-leg of the residual-based reversal strategy.

We find the profits from buying losers (the long-side in the residual-based strategy), after risk adjustment, to load positively and significantly on the lagged aggregate Amihud (2002) illiquidity measure and realized volatility of the S&P500 index. Thus, these profits are more likely reflecting compensations for liquidity provision since they are higher when the level of illiquidity (proxied by the Amihud measure) is high and when the required compensation for liquidity provision is likely to be high (proxied by the realized volatility). Overall, this finding is consistent with the theoretical prediction of Shleifer and Vishny (1992) and the empirical evidence in Coval and Stafford (2007). Recent losers are more likely to be financially distressed and constrained investors are forced to sell, causing a large price concession. The later price recovery thus reflects compensation for liquidity provision. Nagel (2011) also relates short-term return reversal to liquidity provision. Our novel approach allows us to extend Nagel's (2011) analysis by showing that liquidity provision appears more important for explaining the reversal on recent losers since fire sales are more likely than fire purchase. Our results are therefore complementary to the findings in Avramov, Chordia and Goyal (2006) and suggest that liquidity shocks are particularly relevant on the long side.

In contrast, we find the profits from selling winners (the short-side in the residual-based strategy), after risk adjustment, to load positively and significantly on two lagged measures of investor sentiment that reflect optimism and equity overvaluation. The two measures are the monthly number of IPOs and monthly equity share in new issues. Hirshleifer and Jiang (2010) consider security issuance as a proxy for aggregate overvaluation. Baker and Wurgler (2006) also use the number of IPOs and equity issuance in constructing their investor sentiment index.[3] The fact that investor sentiment drives the reversal of recent winners is consistent with the existence of short-sale constraints which limit the ability of rational traders to exploit overpricing immediately (see Miller (1977)). Consistent with Miller's argument, Stambaugh, Yu, and Yuan (2011) show that many asset pricing anomalies are stronger following high levels of sentiment and that this effect is attributable only to the short-legs.[4] Again, by isolating recent "non-fundamental" price change, our analysis shows that Miller's argument also extends to the short-term return reversal, even among large stocks.

The differential role played by liquidity shock and investor sentiment holds up strikingly consistently across ten different subsamples constructed according to stock characteristics such as size, book-to-market, analyst coverage, analyst forecast dispersion, and liquidity. Liquidity shocks always seem to be explaining the reversal on recent losers while investor sentiment always seems to be driving the reversal on recent winners.

The differential role played by liquidity shock and investor sentiment is also confirmed using cross-sectional regression analysis. Using the stock-level Amihud (2002) illiquidity measure, we find that increased stock illiquidity leads to stronger reversal only among recent losers, confirming that liquidity shocks are driving the long-side of reversal profit. When we split our sample into stocks with options traded and stocks without options traded, we find no reversal among recent winners with options traded. Stocks with option traded are less likely to face binding short-sale constraints, hence recent winners with options are less

[3] We do not focus on other components of the sentiment index related to turnover or closed-end fund discount since they might be driven by liquidity as well.

[4] Stambaugh, Yu, and Yuan (2011) did not examine the short-term reversal anomaly.

likely to be overpriced, explaining their lack of reversal in the near future. This result suggests that positive investment sentiment, combined with short-sale constraint, is consistent with the short-side of the reversal profit.

To summarize, in this paper, we take a fresh look at an old asset pricing anomaly: the short-term return reversal. In the process, we make several contributions. First, we forcefully argue that, in order to study the causes of short-term reversal, one should first partial out the well-known effects associated with fundamental news. Second, we propose a novel use of analyst forecast data to proxy for cash-flow news and isolate the component of past return that drives the short-term reversal. Finally, using our "clean" measure of short-term reversal, we are able to show that both liquidity shocks and investor sentiment contribute to the observed short-term reversal, but in different ways: Specifically, the reversal profit is attributable to liquidity shocks on the long side and investor sentiment on the short side.

The rest of the paper is organized as follows. Section 2 discusses our empirical implementation and describes our sample. Section 3 contains the empirical results. Section 4 discusses the differential roles played by investor sentiment and liquidity shock in driving the reversal and Section 5 concludes.

II. Empirical Measurement

A. Expected returns

In order to compute conditional expected stock returns, we need to use a pricing model. To be consistent with the methodology used to risk-adjust returns in our empirical results, we estimate the conditional expected return using the Fama-French (1993) three-factor model:

$$\mu_t = E_t[r_f] + \beta_{MKT,t} E_t[MKT] + \beta_{SMB,t} E_t[SMB] + \beta_{HML,t} E_t[HML] \tag{1}$$

We note, however, that our empirical results do not appear to hinge on the choice of pricing model, (e.g., CAPM or augmented five-factor Fama-French model).

To avoid any look-ahead bias, the factor betas are estimated using monthly returns in the previous five-year rolling window (with a minimum of 36 months of observations) while the factor risk premium is set equal to the average factor return in our sampling period.

B. Cash flow news

To directly compute fundamental cash flow news at monthly frequency, we follow Easton and Monahan (2005) and Da and Warachka (2009) and measure cash flow news using revisions in equity analyst earnings forecasts. Crucially, the use of analyst earnings forecasts allows us to measure cash flow news at monthly frequencies in real time, which is necessary for implementing the short-term reversal strategy. Furthermore, computing monthly revisions mitigates any analyst forecast biases that persist over this short horizon.

We obtain the analyst consensus earnings forecasts from the Institutional Brokers Estimate System (I/B/E/S) Summary unadjusted file. I/B/E/S produces these consensus earnings forecasts each month, typically on the third Thursday of the month. To better match returns to earnings forecast revisions, for most parts of our analysis, we examine the I/B/E/S-month ranging from the current I/B/E/S consensus forecast issuance date (third Thursday this month) to the next consensus forecast issuance date (third Thursday next month), although we do confirm that using the simple calendar month produces very similar results. We initially include all unadjusted consensus earnings forecasts between January 1982 and March 2009. Unadjusted I/B/E/S forecasts are not adjusted by share splits after their issuance date.[5]

We keep consensus earnings forecasts for the current and subsequent fiscal year ($A1_t$, $A2_t$), along with its long-term growth forecast (LTG_t). The earnings forecasts are denominated in dollars per share, and the t subscript denotes when a forecast is employed. The long-term growth forecast represents an annualized percentage growth rate. This forecast has no fixed maturity date but pertains to the next three to five years.

[5] As detailed in Diether, Malloy, and Scherbina (2002), the earnings per share after a share split is often a small number that I/B/E/S rounds to the nearest cent. This rounding procedure can distort certain properties of dollar-denominated analyst forecasts such as revisions and forecast errors.

We first define a simple proxy for the cash flow innovation using only revisions in the earnings forecast for the current fiscal year ($A1_t$):[6]

$$FREV_{t+1} = \begin{cases} \frac{A1_{t+1} - A1_t}{B_t} & \text{for no earnings announcement month} \\ \frac{E1_{t+1} - A1_t}{B_t} & \text{for earnings announcement month} \end{cases}$$

where $E1$ is the actual earnings per share and B_t is the book value per share. In other words, $FREV$ is equal to the analyst forecast revision (scaled) when there is no earning announcement and equal to the earnings surprise (scaled) during the month of fiscal-year earnings announcement.

More precisely, we compute cash flow innovations following Da and Warachka (2009) by taking advantage of multiple earnings forecasts for different maturities. Some modifications are made to account for the fact that we are computing cash flow innovations for individual stocks rather than for portfolios of stocks. We discuss the details below.

Let $X_{t,t+j}$ denote the *expectation* of future earnings (X_{t+j}); here the additional subscript refers to an expectation at time t. A three-stage growth model that parallels the formulation in Frankel and Lee (1998) as well as Pastor, Sinha, and Swaminathan (2008) infers these earnings expectations from analyst forecasts. In the first stage, expected earnings are computed directly from analyst forecasts until year 5 as follows:[7]

$$\begin{aligned} X_{t,t+1} &= A1_t, \qquad (2) \\ X_{t,t+2} &= A2_t, \\ X_{t,t+3} &= A2_t\,(1 + LTG_t), \\ X_{t,t+4} &= X_{t,t+3}\,(1 + LTG_t), \\ X_{t,t+5} &= X_{t,t+4}\,(1 + LTG_t). \end{aligned}$$

Given that LTG_t exceeds 30% for certain stocks, it is unrealistic to assume that such high earnings growth will continue indefinitely. Therefore, we assume that expected earnings growth converges (linearly) to an economy wide steady-state growth rate g_t from year 6 to year 10 in the second stage.

[6] For notational simplicity, we omit the firm-i subscript.

[7] If LTG_t is missing, we set $LTG_t = LTG_{t-1}$. If $A2_t$ is missing, we set $A2_t = A2_{t-1}$. If $A2_{t-1}$ is also missing, we set $A2_t = A1_t(1 + LTG_t)$. If $X_{t,t+3} < 0$, we set $X_{t,t+3} = A1_t(1 + LTG_t)^2$. We exclude stocks / month observations if $X_{t,t+3}$ is missing or negative.

Expected earnings in the second stage are estimated as:

$$X_{t,t+j+1} = X_{t,t+j}\left[1 + LTG_t + \frac{j-4}{5}\left(g_t - LTG_t\right)\right], \tag{3}$$

for $j = 5, \ldots, 9$. The steady-state growth rate g_t is computed as the cross-sectional average of LTG_t.

We also assume the cash flow payout is equal to a fixed portion (ψ) of the ending-period book value. Under this assumption, the clean surplus accounting identity implies that the evolution of expected book value is $B_{t,t+j+1} = (B_{t,t+j} + X_{t,t+j+1})\,(1-\psi)$. The ψ parameter is initially set to 5% since this percentage is close to the average payout rate for the firms in our sample.

In the third stage, expected earnings growth converges to g_t, which implies expected accounting returns converge to $\frac{g_t}{1-\psi}$ beyond year 10. After ten years, the annualized discount factor $\rho = 0.95$ also means that the remaining cash flows exert little influence on the earnings beta estimates.

The expected log accounting return $e_{t,t+j}$ is estimated at time t as:[8]

$$e_{t,t+j+1} = \begin{cases} \log\left(1 + \frac{X_{t,t+j+1}}{B_{t,t+j}}\right) & \text{for } 0 \leq j \leq 9, \\ \log\left(1 + \frac{g_t}{1-\psi}\right) & \text{for } j \geq 10, \end{cases}$$

where the $X_{t,t+j+1}$ expectations are defined in equations (2) and (3).

Consequently, the three-stage growth model implies:

$$E_t \sum_{j=0}^{\infty} \rho^j e_{t+j+1} = \sum_{j=0}^{9} \rho^j e_{t,t+j+1} + \frac{\rho^{10}}{1-\rho} \log\left(1 + \frac{g_t}{1-\psi}\right).$$

Vuolteenaho (2002) shows that the cash flow news are the difference between cash flow expectations over consecutive months; that is:[9]

$$CF_{t+1} = E_{t+1} \sum_{j=0}^{\infty} \rho^j e_{t+j+1} - E_t \sum_{j=0}^{\infty} \rho^j e_{t+j+1} \tag{4}$$

[8] Consistent with our notational convention, $e_{t,t+j}$ denotes the expectation of e_{t+j} at time t. The approximation $E\left[\log\left(1+\frac{X}{B}\right)\right] \approx \log\left(1 + \frac{E[X]}{E[B]}\right)$ ignores a convexity term that is mitigated by computing the necessary innovations.

[9] If there is an earnings announcement during month $t-1$, we make the necessary adjustments because the forecasting horizon is shifted by one year after the announcement. For example, the first term would include the actual announced earnings.

Although earnings forecasts pertain to annual intervals, their revisions are computed over monthly horizons, which helps to mitigate analyst forecast biases that persist over this short horizon.

C. Residual return

We define the residual return as the component of the realized return, in excess of the expected return implied by the pricing model (1), that is not explained by our measure of cash flow news (4):

$$Residual_{t+1} = r_{t+1} - \mu_t - CF_{t+1}. \tag{5}$$

The residual return in (5), by purging the realized return of fundamental cash flow and expected return components, help to isolate the portion of the return due to sentiment and liquidity which is more likely to revert.

Measurement error/mis-specification, especially in the cash flow news model, of course remains a concern for the empirical implementation. In what follows, we therefore document in great detail that our qualitative results do not change if we use simpler cash flow news definitions. Moreover, for the measurement error to drive the predictability of future returns, one would expect to see a strong correlation between our cash-flow news measure and the reversal of the residual return. We find this not to be the case in the data.

D. Sample description

Our final sample consists of stock / month observations where the expected return and cash flow news can all be computed. Table 1 provides a summary statistics for the sample. On average, there are about 2350 stocks in our sample each month, but numbers increase over time.

While the stocks in our sample represent only one-third of the total number of stocks in the Center for Research in Security Prices (CRSP) database, we cover almost 75% of the US stock universe by market capitalization. In fact, our average capitalization of stocks in our sample is about \$2.5 billion, twice that of an average stock in CRSP. Stocks in our sample also receive high analyst coverage, with an average of eight analyst reports per month. To alleviate the impact of any market microstructure-related noise, we exclude stock / month observations if a stock's monthly closing price is below $5 at the time of portfolio formation. Overall, our sample therefore consists of relatively large and liquid stocks receiving high analyst coverage, implying that our results are unlikely to be driven by positions in extremely small and illiquid stocks.

For industry classification, we use the two-digit I/B/E/S SIGC code, which classifies all stocks into 11 industries: finance, health care, consumer non-durables, consumer services, consumer durables, energy, transportation, technology, basic industries, capital goods, and public utilities.

III. Empirical Results

For comparison, we first implement the Jegadeesh (1990) short-term reversal strategy, which sorts stocks into deciles on the basis of their prior-month returns, and then buys stocks in the bottom decile (losers) and sells stocks in the top decile (winners). This zero-investment strategy is rebalanced every month. Its average raw return and risk-adjusted returns are reported in Panel A of Table 2.

In our sample, which covers larger stocks and a more recent period, the standard reversal strategy generates a raw return of 0.67% per month (t-value = 2.53), which is much lower than the 2.49% return documented in Jegadeesh (1990). After risk adjustment the profit is even smaller, and the three-factor alpha drops to 0.33% per month with an insignificant t-value of 1.37. When we also include the Carhart (1997) momentum factor (MOM) and a fifth short-run reversal factor (DMU), the alpha is essentially zero as expected. Given this evidence, one could argue that short-term return reversal has become less likely recently among all but the smallest stocks, at least economically.

Moskowitz and Grinblatt (1999) document a strong industry momentum, in that current winner industries outperform current loser industries in the subsequent month. As a result, a within-industry reversal strategy should perform better. This is indeed the case as reported in Panel B of Table 2. When we sort stocks into deciles within each industry on the basis of their prior-month returns, and buy losers / sell winners within each industry, this within-industry reversal strategy generates a return of 1.20% per month (t-value = 5.87). Risk adjustments reduce but do not eliminate the profit. For example, the three-factor alpha is 0.92% per month with a t-value of 5.11, and the five-factor alpha is 0.46% with a t-value of 2.77. These results suggest that stock prices overreact to firm-specific information and that the overreaction is significant even among large stocks for the more recent years.

Finally, we sort stocks into deciles within each industry by prior-month residual returns. We then buy stocks in the bottom decile (with the most negative residual return) and sell stocks in the top decile (with the most positive residual return). We label this modified reversal strategy our *benchmark residual-based reversal strategy*.

The benchmark residual-based reversal strategy indeed performs the best, as reported in Panel C of Table 2. It generates a return of 1.57% per month (t-value = 9.48). The profit is still large and highly significant even after risk adjustment. For example, the three-factor alpha is 1.34% per month with a t-value of 9.28, and the five-factor alpha is 0.91% with a t-value of 6.02.

A visual comparison between our benchmark residual-based reversal strategy and the standard reversal strategy is provided in Figure 1. Panel A plots the time series of raw returns of the two strategies in the sample from 1982 through 2009, and Panel B plots their three-factor adjusted returns.

Our benchmark residual-based reversal strategy clearly dominates; its return series are both higher on average and much less volatile. As a result, our benchmark residual-based reversal strategy has a much higher Sharpe ratio. For raw returns, the monthly Sharpe ratio is 0.52 for the benchmark residual-based reversal strategy and only 0.14 for the standard reversal strategy. For the three-factor adjusted returns, the monthly Sharpe ratio is 0.53 for the benchmark residual-based reversal strategy and only 0.08 for the standard reversal strategy.

A. Subsample and robustness results

Panel A of Table 3 shows the performance of the benchmark residual-based reversal strategy when we increase the holding horizon from one month to five months. We find that the profit is short term in nature and accrues mainly during the first month after portfolio formation. The profit drops from 1.57% (t-value = 9.48) during the first month after portfolio formation to 0.40% (t-value = 2.51) during the second month. Beyond that, the profit drops to essentially zero. The short-term nature of the trading profit suggests that it is unlikely due to some missing risk factor because we do not expect the systematic risk exposure to vary drastically at monthly frequency post-portfolio formation.

So far we have used the I/B/E/S month, which runs from the current I/B/E/S consensus forecast issuance date to the next consensus forecast issuance date. This allows us to better match monthly return to monthly cash flow news measured using consensus earnings revisions. A potential problem is that different I/B/E/S months may have very different numbers of days. Although we do not think this problem will lead to any systematic bias in our results, we repeat the analysis using calendar-month returns as a robustness check. In other words, we compute the residual return using the return in calendar month t and cash flow news in I/B/E/S month t (from the third Thursday in calendar month $t-1$ to the third Thursday in calendar month t). As it turns out, when we use calendar-month returns and repeat the benchmark residual-based reversal strategy, the profit actually improves as reported in Panel B of Table 3. For example, the raw return increases to 1.74% per month (t-value = 10.57). The three- and five-factor alpha increase to 1.63% per month (t-value = 10.29) and 1.47% per month (t-value = 12.96), respectively.

A well-documented problem associated with stocks traded at low prices is that the bid-ask bounce can lead to a non-negligible upward bias in the average return computation, as Blume and Stambaugh (1983) discuss. To ensure that our results are not unduly affected by the bid-ask bounce, we follow Subrahmanyam (2005) among others and examine calendar-month returns computed using mid-quotes. The results, presented in Panel C of Table 3, show that the residual-based reversal strategy evaluated using mid-quote-based calendar-month returns delivers an even higher profit. For example, the raw return increases to 2.11% per month (t-value = 9.15) while the three- and five-factor alpha increase to 1.97% per month (t-value = 8.72) and 1.79% per month (t-value = 9.06), respectively. As an alternative way to control for the bid-ask bounce, we exclude the first trading day in the holding period when computing holding-period portfolio returns. Unreported results suggest that our residual-based reversal strategy remains highly profitable. For example, the raw return, the three- and five-factor alpha are 1.51% per month (t-value = 8.67), 1.26% per month (t-value = 8.45), and 0.81% per month (t-value = 4.98), respectively.

We make several parametric assumptions in computing the cash flow news. Do our main results depend on these assumptions? To answer this question, we consider a simple non-parametric way of identifying stocks that recently experienced large residual returns: We look for stocks whose prices and earnings forecasts were revised in opposite directions during the previous month. To the extent that an earnings forecast revision ($FREV$) proxies for the direction of the true cash flow shock, a large but opposite movement in price must reflect large residual returns (in absolute terms).

To implement this idea, we consider a 3 by 3 within-industry double-sort strategy, sorting first on the basis of prior-month stock returns and then on the basis of prior-month earnings forecast revisions. We then buy past losers with upward forecast revisions and sell past winners with downward forecast revisions, and hold the resulting position for one month.

Interestingly, this strategy generates similar profits, as reported in Panel D of Table 3. For example, the double-sort strategy generates a return of 1.86% per month (t-value = 12.05) with three- and five-factor alphas of 1.72% per month (t-value = 12.24) and 1.11% per month (t-value = 7.22), respectively. Moreover, the time series correlation between this non-parametric residual strategy and the parametric residual strategy is very high ($\rho = 0.76$), consistent with a conclusion that the alternative strategies capture similar effects from residual returns.

Jegadeesh (1990) documents that a reversal strategy is much more profitable in the month of January. As a robustness check, we also report in Panel A of Table 4 the results after removing January from the sample. The profits are only slightly weakened.

Panel B of Table 4 reports the reversal profits across three subsample periods: 1982-1989, 1990-1999, and 2000-2009. We find reversal profits to be always positive and significant, even after the three-factor adjustment. Over time, the profits decline, consistent with the improvement of overall market liquidity and/or price efficiency.

Panel C of Table 4 suggests that the benchmark residual-based reversal strategy generates significantly positive profit in each of the 11 industries, with t-values ranging from 3.81 to 6.45.

We also examine whether the result may vary depending on stock characteristics. Each month, we sort stocks in the sample into three groups on the basis of a stock characteristic: size, book-to-market ratio (BM), analyst coverage (NOA), analyst forecast dispersion (DISP), and the Amihud (2002) illiquidity measure (Liquidity). We then implement our benchmark residual-based reversal strategy in each group. To save space, we report the results for only top and bottom groups in Panel D.

We first note that the residual-based reversal strategies are highly profitable in each of the subsamples. The profit is higher among smaller stocks, value stocks, illiquid stocks, and stocks covered by fewer analysts.

To alleviate potential concerns that our results are driven by post-earnings-announcement drift (PEAD), we also exclude all stock / month observation if there is an earnings announcement for that stock. Panel E of Table 4 suggests that such an exclusion hardly changes our results.

Overall, the superior performance of the benchmark residual-based reversal strategy once again confirms the within-industry residual return to be the main driver of short-term return reversal. Unreported results confirm the importance of residual return using Fama-MacBeth (1973) cross-sectional regressions. By isolating the main driver, the benchmark residual-based reversal strategy provides us with a new and superior testing ground for the two leading explanations of the short-term return reversal. But first, we take a closer look at individual stock characteristics across different portfolios underpinning the residual-based reversal strategy.

B. Portfolio characteristics

Table 5 reports average portfolio characteristics across the decile portfolios sorted on within-industry non-cash-flow shock (residual). Stocks in portfolio 1 on average experienced a large negative residual return ($residual$ = -18.07%) during the formation month (0). The negative residual return comes from a positive cash flow shock (5.51%) but at the same time a large negative return (-11.32%). Stocks in portfolio 10, however, on average experienced a large positive residual return ($residual$ = 24.57%) during the formation month (0). The positive residual return comes from a negative cash flow shock (-8.99%) but at the same time a large positive return (16.75%).

The large return movements (in the opposite directions of cash flow news) are unlikely to be driven by liquidity shocks alone. Although the two extreme portfolios (portfolios 1 and 10) have slightly higher expected returns (1.24% and 1.17%, respectively), the cross-portfolio variation in the expected returns is small. As we saw in the trading strategy results (Table 2, Panel C), portfolio 1 outperforms portfolio 10 during the first month after portfolio formation. As seen in Table 5, both raw returns and the three-factor alphas decline monotonically in within-industry residual return, suggesting that residual return indeed is a strong predictor of future stock return reversals.

The two extreme portfolios also hold stocks that are relatively small and illiquid, and receive less coverage by analysts than the average stock in our sample. Their average market caps are about one-half those of other stocks in our sample, and their average trading prices are also lower ($30.90 for portfolio 1 and $38.35 for portfolio 10), although they are clearly not penny stocks. Stocks in the extreme portfolios trade more actively according to the turnover measure but are also more illiquid as measured by the Amihud (2002) measure and are covered by fewer than the average of eight analysts. These characteristics are consistent with the idea that liquidity shock is a key driver of the reversal profit, although we cannot completely rule out the explanation based on sentiment-driven mispricing.

A trading strategy of buying portfolio 1 and selling portfolio 10 is associated with very high portfolio turnover. On average, 90.2% of the stocks in portfolio 1 and 90.8% of the stocks in portfolio 10 are turned over every month. Such a high turnover is to be expected, because extreme divergence between returns and cash flow news is rather rare, and neither is expected to persist.[10] The extreme portfolios are also associated with higher percentage quoted bid-ask spreads of 46 basis point and 43 basis points, respectively.

The portfolio turnover ratios and bid-ask spreads together provide a rough transaction cost estimate of $46\times 90.2\% + 43\times 90.8\% = 80.5$ basis points per month for the trading strategy. This estimate is much lower than the risk-adjusted return of our residual-based trading strategy (three-factor alpha = 1.34% per month, t-value of 9.28), suggesting that our reversal profit is also economically significant (transaction cost adjusted alpha $\approx 0.54\%$ per month, t-value of 3.9) and not likely simply a manifestation of market microstructure effects.

If our risk-adjusted profit is higher than a reasonable estimate of transaction cost, why is it not arbitraged away immediately? One reason is related to the limit to arbitrage (Shleifer and Vishny (1997)). Table 5 suggests that a common proxy for the limit to arbitrage, idiosyncratic volatility is the highest for the two extreme portfolios (see Ang, Hodrick, Xing, and Zhang (2006)). Thus uncertainty may prevent a risk-averse arbitrageur from trading and eliminating mispricing immediately.

[10] A risk factor based explanation on the other hand would not be consistent with such high turnover.

IV. Liquidity Shock *vs.* Investor Sentiment

Our residual-based reversal strategy outperforms the standard reversal strategy since the residual component, after controlling for cash flow news, better isolates price movements due to investor sentiment or liquidity shocks that are more likely to revert soon. Do liquidity shock and investor sentiment play different roles in driving the short-term reversal? We address this question in this section.

A. Time-series evidence

We first use a time-series regression approach similar to those used in Stambaugh, Yu, and Yuan (2011). Specifically, we regress the excess returns in month t on the Fama-French (1993) three-factors in month t and other market-level variables in month t-1.

The first two variables are related to liquidity. The first is a detrended Amihud measure (amihud) constructed from the difference between the average Amihud (2002) illiquidity measure and its moving average in the previous 12 months. The stock market in US has experienced several episodes of liquidity improvement recently such as decimalization in 2000, making the level of Amihud measure less comparable over time. The detrended Amihud measures controls for such a time trend and can be interpreted as a measure of "abnormal" illiquidity. The second measure is the realized volatility on the S&P 500 index (rv) calculated in month t as the annualized realized return standard deviation: $\sqrt{\frac{252}{N_t}\sum_{i=1}^{N_t} r_i^2}$ where N_t is the number of trading days in month t. Nagel (2011) argued that stock market volatility is related to the required compensation for liquidity provision. In particular, he examines the VIX index. While we use realized volatility instead (since the VIX index is only available more recently), we also verify that we obtain very similar results using VIX within the shorter sampling period, which is not surprising given the very high monthly correlation between the realized volatility and the VIX index.

The next two variables are related to investor sentiment, in particular, investor optimism which likely leads to equity overvaluation. The first is the monthly number of initial public offerings (nipo), and the second is the monthly equity share in new issues (s), defined as the share of equity issues in total equity and debt issues. Both nipo and s are used by Baker and Wurgler (2006) in constructing their investor sentiment index. We do not focus on other components of the sentiment index related to turnover or closed-end fund discount since they arguably are closely related to liquidity. Hirshleifer and Jiang (2010) also consider security issuance as a proxy for aggregate overvaluation.

The time series regression results are reported in Table 6. The sample period is from January 1982 through March 2009. The t-statistics reported in parentheses are Newey and West (1987) adjusted with twelve lags. In Panel A, we examine the standard Fama-French short-term reversal factor as the dependent variable.[11] We find that the reversal factor, after the three-factor risk adjustment, to only load positively and significantly on the lagged detrended Amihud. It loads negatively on lagged nipo and s, although not significantly. In Panel B, we examine the profit to our residual-based strategy and find it to also load positively and significantly on the lagged volatility.

Panel C and D study the excess return to buying losers (or the long-side) and to selling winners (or the short-side) in our residual-based strategy separately. This separation yields very interesting results. We find the profits from buying losers or the long-side in residual-based strategy, after risk adjustment, to load positively and significantly on the lagged detrended Amihud and lagged realized volatility on the S&P500 index. The *t*-values on these two variables are much higher in Panel C than in the previous two panels. Thus, these profits are more likely reflecting compensations for liquidity provision since they are higher when the level of illiquidity (proxied by the Amihud measure) is high and when the required compensation for liquidity provision is high (proxied by the realized volatility). Overall, this finding is consistent with the theoretical prediction of Shleifer and Vishny (1992) and the empirical evidence in Coval and Stafford (2007). Recent losers are more likely to be financially distressed and constrained investors are forced to sell, causing a large price concession. The later price recovery thus reflects compensation for liquidity provision. The investor sentiment variables nipo and s do not seem relevant in explaining the risk-adjusted return to buying recent losers.

In sharp contrast, we find the profits from selling winners or the short-side in residual-based strategy, after risk adjustment, to load positively and significantly on two lagged measures of investor sentiment. The *t*-values on both nipo and s are positive and highly significant, suggesting larger price decline following periods when investors are more optimistic and as a result the stock market is more overvalued. The fact that investor sentiment drives the reversal on recent winners is consistent with the existence of short-sale con-

[11] The Fama-Frech short-term reversal factor is defined as the average return on the two low prior return portfolios minus the average return on the two high prior return portfolios, or $1/2(SmallLow + BigLow) - 1/2(SmallHigh + BigHigh)$.

straints which limit the ability of rational traders to exploit overpricing immediately (see Miller (1977)). As Miller argues (p. 1154), “a market with a large number of well informed investors may not have any grossly undervalued securities, but if those investors are unwilling to sell short (as they often are) their presence is consistent with a few investments being overvalued.” Consistent with Miller’s argument, Stambaugh, Yu, and Yuan (2011) show that many asset pricing anomalies are stronger following high levels of sentiment and this effect is attributable only to the short-legs. Again, by isolating recent “non-fundamental” price changes, our approach shows that Miller’s argument also extends to the short-term return reversal, even among large stocks.

Figure 2 provides a graphical representation of the results. In this figure, we plot a smoothed time series of the risk-adjusted returns to buying losers (long alpha) and selling winners (short alpha) in our residual-based strategy against each of the four market-level variables. We find short alpha to be highly correlated with nipo and s (correlations are 0.43 and 0.57). In contrast, long alpha is not correlated with nipo and s (correlations are -0.10 and -0.03). On the other hand, long alpha is highly correlated with detrended Amihud and realized volatility (correlations are 0.24 and 0.23) while short alpha is not.

We repeat these time-series regressions in each of the 10 subsamples of stocks constructed by sorting on various stock characteristic such as size, book-to-market ratio, analyst coverage, analyst forecast dispersion, and the Amihud (2002) illiquidity measure. To save space, in Table 7, we only report the coefficients and t-statistics on the two lagged liquidity variables (amihud and rv) and the two lagged sentiment variables (nipo and s). While the t-statistics on these variables are in general smaller than those reported in Table 6 due to the fact that we have less stocks in each subsample, the general pattern is remarkably consistent across the ten subsamples. In general, amihud and rv always carry positive and significant loadings for the long-side of the reversal while nipo and s always carry positive and significant loadings for the short-side. Not surprisingly, across these different subsamples, we also find the liquidity variables to be more important for small and illiquid stocks with high analyst forecast dispersion.

B. Cross-sectional evidence

We confirm the differential roles played by liquidity and sentiment using cross-sectional regressions.

If liquidity is the driving force behind the reversal profit to recent losers, we would expect to see stronger reversal following negative residual returns among more illiquid stocks. We test this prediction in Panel A of Table 8. We run Fama-MacBeth (1973) cross-sectional regressions for past losers and past winners. Past losers (winners) are those stocks with previous-month residual returns in the bottom (top) 30%. The dependent variable is stock return in the next month. The independent variables include two interaction terms: residual interacted with amihud_low and amihud_high respectively, where residual denotes the residual return in previous month. Amihud_low (amihud_high) is a dummy variable equals to 1 if the stock's Amihud (2002) illiquidity measure is below (above) median. Other control variables include beta, log(size), log(BM), and turnover. We find that the coefficients on all four interaction terms are negative and significant, confirming short-term return reversals everywhere. Moreover, the coefficients are more negative among more illiquid stocks with amihud_high=1, indicating stronger reversal. Most importantly, we observe significantly more negative coefficients among more illiquid stocks only among past losers, confirming that the long-side of reversal profit is driven by illiquidity.

To examine the role played by the investor sentiment, we note that the short-sale constraint is the necessary condition for positive sentiment to induce over-pricing. It is then natural to expect sentiment to induce overpricing only among stocks with binding short sale constraint. For stocks without short-sale constraints, overpricing is unlikely, and we therefore should not expect reversal for recent winners. To test this prediction, in Panel B, we focus on residual return interacted with dummy variables indicting option trading on the same stock. Specifically, option_no is a dummy variable equal to 1 if there is no option traded on the stock, and option_yes is another dummy variable defined as 1 if options are trading on the stock. Confirming our conjecture, among recent winners, we only observe significant reversals among stocks without options. For stocks with options, there is no significant reversal.

To summarize, both time-series and cross-sectional results in this section suggest that liquidity shocks are more likely to affect recent losers while investor sentiment is more likely to affect recent winners.

V. Conclusion

Identifying the causes of short-term return reversal has important implications for empirical asset pricing tests, and more generally for understanding the limits of market efficiency. While financial economists have long studied the profitability of a contrarian strategy of buying recent losers and selling recent winners, we have not had a complete understanding of what is driving short-term reversal profits. In this paper, we shed some new light on the economic drivers of short-term reversal profits by focussing on past return residuals that are unexplained by measures of "fundamental" news.

Proxying for cash flow shocks using analyst earnings forecast revisions, we find an enhanced short-term reversal strategy based on past residual returns to be highly profitable over the 27-years of our sample of large stocks with analyst coverage. This simple short-term return reversal trading strategy generates a three-factor alpha of 1.34% per month (t-value = 9.28), four times the alpha of the standard short-term reversal strategy.

Our results suggest that short-term return reversal is pervasive and much greater than previously documented. In addition, we provide strong empirical evidence that liquidity shocks are likely to drive the reversals of recent losers while investor sentiment is more likely to drive reversals of recent winners.

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Figure 1. Components of short-term return reversal profit. The time series of raw returns (top panel) and Fama-French (1993) three-factor adjusted returns (bottom panel) for the standard reversal strategy (dotted) and the benchmark residual-based reversal strategy (solid).

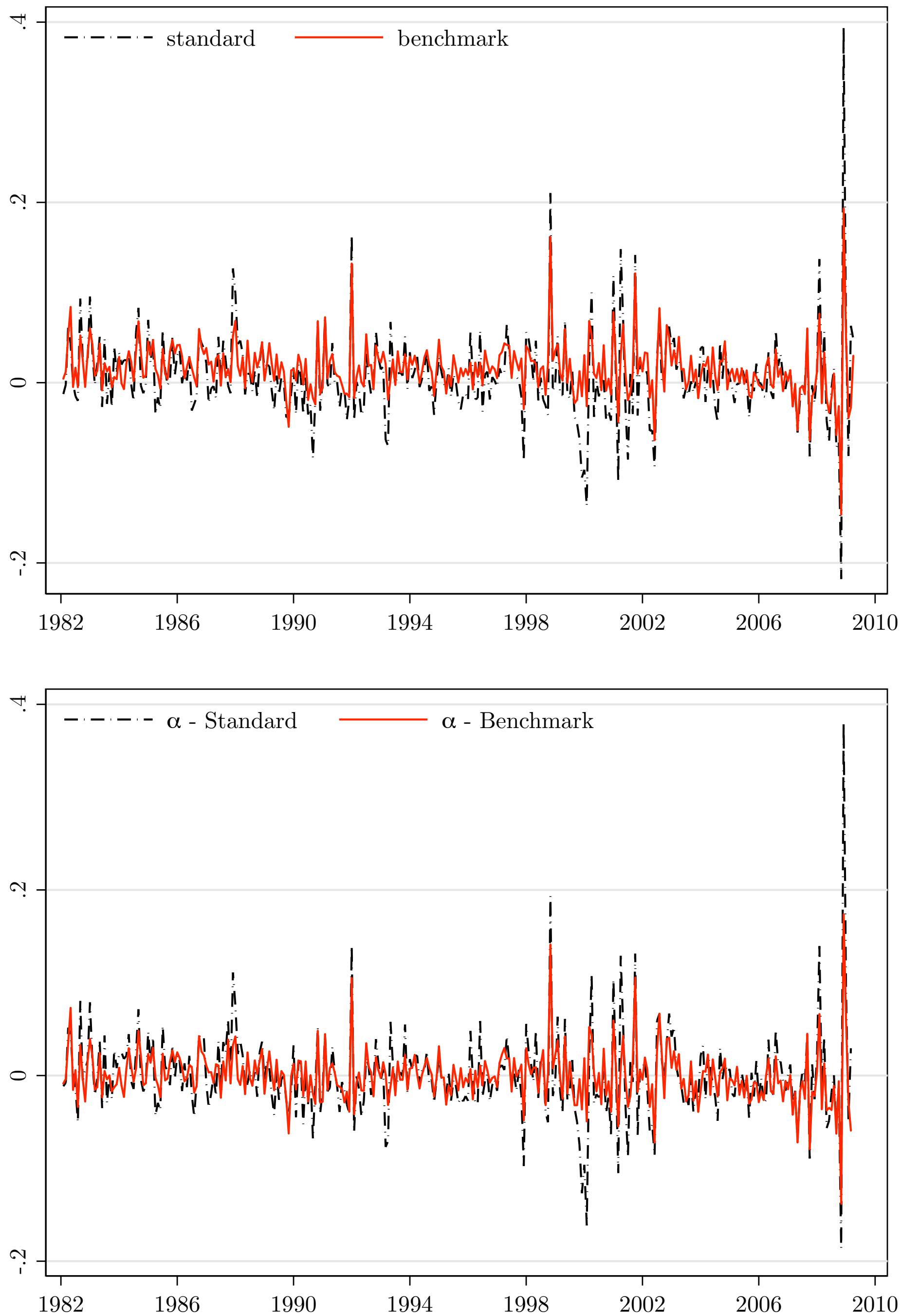

Figure 2. Time series of Fama-French (1993) three-factor adjusted returns. Risk adjusted returns on the long and short portfolios of the benchmark residual-based reversal strategy are plotted separately against the time series of the number of IPOs (nipo), net share issuance(s), the realized volatility on the S&P500 index (RV SP500), and the detrended Amihud measure (Detrended Amihud). All time series are smoothed using moving averages of 12 months.

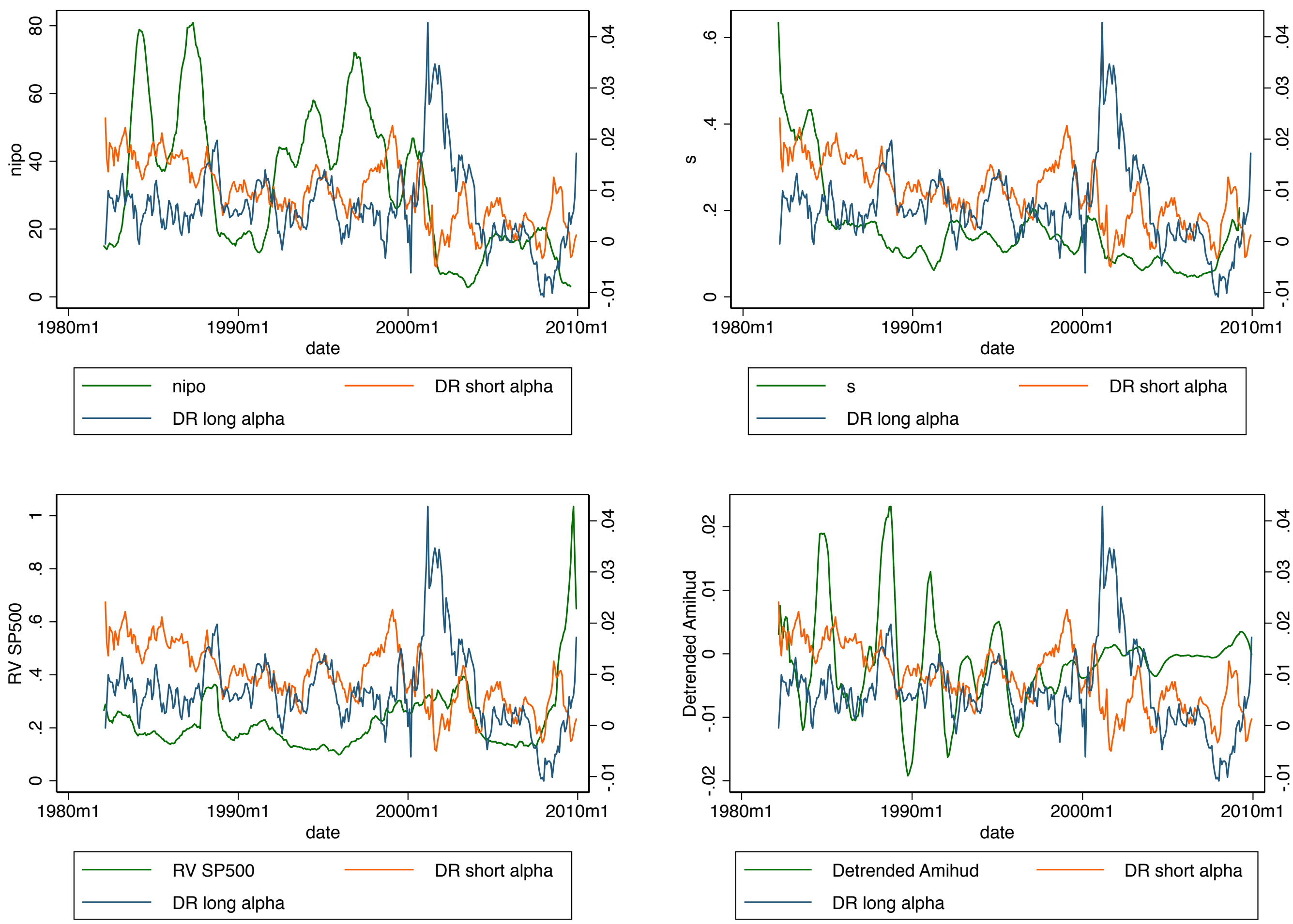

Table 1

Characteristics of the sample. Reported are several characteristics of the stock sample from the Institutional Brokers Estimate System (I/B/E/S) Summary unadjusted file used in our empirical analysis. The full sample period is from January 1982 through March 2009. The stock-level characteristics are: mean and median size (in millions of dollars), mean and median book-to-market ratio (BM), and mean and median number of analyst earnings reports per month. To avoid the bias caused by outliers, we winsorize the BM values at the 99th percentile each month. Our sample is compared to the CRSP database on the number of stocks included and the average size. Percent of market capitalization measures the total market value of all stocks in our sample relative to total market value of all stocks in CRSP. The full sample period is also divided into three subsampling periods: January 1982 through December 1989, January 1990 through December 1999, and January 2000 through March 2009.

Number of months	Mean size	Median size	Mean BM	Median BM	Mean analyst coverage	Median analyst coverage	Average number of stocks	Percent of market capitalization	Average number of stocks in CRSP	Mean size of CRSP stocks	Median size of CRSP stocks
327 (Jan 1982-Mar 2009)	2523.75	416.40	1.84	0.86	7.99	5.48	2354.82	73.79%	7133.84	1224.25	120.46
96 (Jan 1982-Dec 1989)	961.78	227.18	1.14	0.85	8.99	6.09	1667.67	70.59%	6416.15	352.67	37.21
120 (Jan 1990-Dec 1999)	1969.75	302.12	1.68	0.76	8.01	5.36	2564.42	74.45%	7938.72	869.97	81.92
111 (Jan 2000-Mar 2009)	4473.56	703.60	2.61	0.98	7.11	5.08	2722.51	75.85%	6884.41	2361.05	234.12

Table 2

Reversal trading strategies. Raw returns and risk-adjusted returns for three portfolio trading strategies: the standard reversal strategy (Panel A), the within-industry reversal strategy (Panel B), and the benchmark residual-based reversal strategy (Panel C). The standard reversal strategy sorts stocks into deciles according to prior-month returns, and then buys stocks in the bottom decile (losers) and sells stocks in the top decile (winners). The portfolio is rebalanced every month. The within-industry (benchmark residual-based) reversal strategy sorts stocks into deciles within each industry according to prior-month returns (residual return), and buys losers / sells winners within each industry. The factors to adjust raw returns are the Fama-French (1993) three factors (mkt-r_f, smb, and hml), the Carhart (1997) momentum factor (mom), and the short-run reversal factor (dmu) which is constructed from the daily short-term reversal factor available at French's website. The sample period is from January 1982 through March 2009. T-statistics are reported in parentheses.

Intercept	mkt-r_f	smb	hml	mom	dmu
Panel A: Standard reversal					
0.67%					
(2.53)					
0.33%	0.4972	0.0169	0.2280		
(1.37)	(9.29)	(0.19)	(2.78)		
-0.19%	0.2178	0.0063	0.0520	-0.3794	0.4441
(-0.85)	(5.00)	(0.09)	(0.82)	(-7.94)	(9.95)
Panel B: Within industry reversal					
1.20%					
(5.87)					
0.92%	0.3849	0.1131	0.1904		
(5.11)	(9.66)	(1.69)	(3.12)		
0.46%	0.1824	0.1065	0.0688	-0.2526	0.3455
(2.77)	(5.55)	(2.11)	(1.44)	(-7.01)	(10.26)
Panel C: Within industry residual-based reversal					
1.57%					
(9.48)					
1.34%	0.3290	0.0595	0.1474		
(9.28)	(10.31)	(1.11)	(3.01)		
0.91%	0.2048	0.0575	0.0843	-0.1126	0.2562
(6.02)	(6.89)	(1.26)	(1.95)	(-3.45)	(8.41)

Table 3: **Within-industry residual-based reversal: robustness check.** Panel A reports the portfolio returns during each of the five months post-portfolio formation. Panel B reports raw and risk-adjusted returns for the benchmark residual-based reversal strategy when portfolio returns and discount news are based on calendar months. Panel C calculates daily returns using midpoints of closing bid and ask prices and monthly returns by cumulating the daily midpoint returns within a month. We report raw and risk-adjusted returns for the benchmark residual-based reversal strategy based on these monthly returns. Panel D reports raw and risk-adjusted returns for a 3 by 3 within-industry double-sort strategy, first sorted into three groups according to prior-month stock returns (top 30%, middle 40%, and bottom 30%) and then according to prior-month earnings forecast revisions (top 30%, middle 40%, and bottom 30%). We then buy past losers with upward forecast revisions and sell past winners with downward forecast revisions, and hold the positions for one month. The factors to adjust raw returns are the same as in Table 4. The sample period is from January 1982 through March 2009. T-statistics are reported in parentheses.

Panel A: Long-horizon returns					
Portfolio holding months	1st month raw return	2nd month raw return	3rd month raw return	4th month raw return	5th month raw return
	1.57%	0.40%	-0.05%	-0.03%	0.13%
	(9.48)	(2.51)	(-0.38)	(-0.26)	(0.97)
Panel B: Using calendar-month return					
Intercept	mkt-r_f	smb	hml	umd	dmu
1.74%					
(10.57)					
1.63%	0.2364	-0.0106	0.0960		
(10.29)	(6.37)	(-0.20)	(1.68)		
1.47%	0.0856	-0.0592	0.0273	0.0479	0.6307
(12.96)	(3.14)	(-1.63)	(0.68)	(1.78)	(18.25)
Panel C: Using returns based on quote midpoints					
2.11%					
(9.15)					
1.97%	0.2734	0.0516	0.1481		
(8.72)	(5.11)	(0.70)	(1.83)		
1.79%	0.1142	-0.0001	0.0733	0.0539	0.6469
(9.06)	(2.37)	(-0.00)	(1.05)	(1.15)	(10.73)
Panel D: Double-sort on return and earnings forecast revision					
1.86%					
(12.05)					
1.72%	0.2742	-0.0300	0.0174		
(12.24)	(8.79)	(-0.57)	(0.36)		
1.11%	0.1858	-0.0270	-0.0034	0.0099	0.2770
(7.22)	(6.17)	(-0.58)	(-0.08)	(0.30)	(8.98)

Table 4: **Within-industry residual-based reversal: Subperiod and subsample results.** Excluding January months (Panel A), Three decade subsamples (Panel B), I/B/E/S Industry subsamples (Panel C), characteristics based subsamples (Panel D), and excluding earnings-announcement months (Panel E). In Panel D, stocks are sorted into three groups by characteristic: top 30%, middle 40%, and bottom 30%. We report the profits for the top and bottom groups, and their differences. The characteristics are: market capitalization, book-to-market ratio, Amihud (2002) illiquidity measure, analyst coverage count, analyst forecast dispersion (defined as the ratio of the standard deviation to the absolute value of the median of analyst earnings forecasts). In Panel E, we exclude stock / month observations if there is an earnings announcement on the stock. T-statistics are reported in parentheses.

	Unadj. Profit	3f alpha	5f alpha
Panel A: Excluding January			
Jan 1982-Mar 2009	1.41%	1.23%	0.81%
	(8.30)	(8.27)	(5.18)
Panel B: Subperiods			
Jan 1982-Dec 1989	2.10%	2.00%	1.46%
	(9.58)	(8.66)	(5.04)
Jan 1990-Dec 1999	1.64%	1.33%	0.43%
	(6.90)	(6.29)	(1.37)
Jan 2000-Mar 2009	0.99%	1.04%	0.64%
	(2.74)	(3.32)	(2.33)
Panel C: Industry			
Finance	1.77%	1.37%	0.42%
	(5.70)	(4.85)	(1.38)
Health Care	1.41%	1.12%	0.96%
	(4.24)	(3.42)	(2.45)
Consumer Non-durables	1.57%	1.23%	0.69%
	(4.97)	(4.12)	(1.97)
Consumer Services	1.36%	1.19%	0.66%
	(5.27)	(4.82)	(2.33)
Consumer Durables	1.60%	1.31%	0.63%
	(4.08)	(3.51)	(1.39)
Energy	1.96%	1.92%	1.93%
	(6.24)	(5.99)	(4.92)
Transportation	1.76%	1.54%	1.11%
	(3.90)	(3.40)	(2.00)
Technology	1.20%	1.04%	0.62%
	(4.47)	(3.88)	(1.94)
Basic Industries	1.74%	1.61%	1.30%
	(6.43)	(6.01)	(3.94)
Capital Goods	1.87%	1.52%	1.10%
	(6.45)	(5.65)	(3.73)
Public Utilities	0.99%	0.84%	0.57%
	(3.81)	(3.25)	(1.92)

Table 4 continued

	Unadj. Profit	3f alpha	5f alpha
Panel D: Characteristic-sorted portfolio			
Size			
Small	2.07%	1.91%	1.55%
	(9.05)	(8.58)	(5.86)
Large	0.94%	0.73%	0.28%
	(5.67)	(4.80)	(1.67)
Difference	1.13%	1.18%	1.27%
	(4.76)	(4.88)	(4.26)
BM			
Value	1.83%	1.66%	1.51%
	(8.97)	(8.59)	(6.49)
Growth	1.23%	1.00%	0.70%
	(5.39)	(4.54)	(2.80)
Difference	0.58%	0.66%	0.81%
	(2.40)	(2.70)	(2.70)
# Analysts (NOA)			
Low	1.72%	1.60%	1.11%
	(8.67)	(8.34)	(4.97)
High	1.20%	0.97%	0.48%
	(6.37)	(5.71)	(2.55)
Difference	0.53%	0.63%	0.63%
	(2.40)	(2.85)	(2.32)
Analyst dispersion (DISP)			
Low	1.81%	1.81%	1.37%
	(9.23)	(8.84)	(5.36)
High	1.45%	1.13%	0.50%
	(6.10)	(4.69)	(1.68)
Difference	0.37%	0.68%	0.87%
	(1.32)	(2.38)	(2.38)
Liquidity			
Illiquid	2.38%	2.23%	1.67%
	(11.81)	(11.45)	(7.39)
Liquid	0.91%	0.68%	0.29%
	(4.92)	(3.99)	(1.47)
Difference	1.48%	1.55%	1.39%
	(7.05)	(7.23)	(5.26)
Panel E: Excluding the earnings-announcement months			
	1.81%	1.58%	1.11%
	(9.84)	(9.67)	(6.35)

Table 5

Characteristics of residual-return-sorted decile portfolios. Portfolio 1 has a large negative residual return during the formation month (0), while Portfolio 10 has a large positive residual return. Ret(0) is the simple average monthly portfolio returns in the portfolio formation month, measured in percentage terms. ER is the conditional expected return based on rolling betas estimated from monthly returns in the previous five-year rolling window. CF rev measures the within-industry cash flow shock, where the cash flow news is measured by the analyst consensus earnings forecasts as in Da and Warachka (2009). Ret(+1) and 3-factor alpha are the simple average monthly portfolio raw and Fama-French (1993) three-factor adjusted returns in the portfolio holding month, respectively. Price, Size, BM, and NoA are the simple average of price, market capitalization (in millions of dollars), book-to-market ratio, and analyst coverage count, respectively. To avoid the bias caused by outliers, we winsorize the BM values at the 99th percentile each month. IVOL is the simple average of the monthly idiosyncratic volatility for all stocks included in the portfolio formation month, where monthly idiosyncratic volatility is constructed from the standard deviation of daily residuals from the Fama-French (1993) three-factor model. Turnover is defined as the trading volume divided by the number of shares outstanding. Amihud illiquidity measures stock illiquidity as in Amihud (2002). Portfolio turnover measures the proportion of stocks that are not in the same residual-sorted portfolios in two consecutive months. Spread measures the simple average of the quoted bid-ask spread for stocks included in the same decile portfolio. The sample period is from January 1982 through March 2009.

	residual	Ret (0)		CF rev	Ret(+1)	3-factor					IVOL	Turnover	Amihud	Portfolio	Spread
Portfolio	(%)	(%)	ER (%)	(%)	(%)	alpha (%)	Price	Size	BM	NoA	(%)	(%)	illiquidity	Turnover	(%)
1	-18.07	-11.32	1.24	5.51	1.90	0.66	30.90	1659.98	1.72	7.32	9.99	14.70	0.22	90.18	0.46
2	-8.34	-6.52	1.16	0.66	1.63	0.50	38.36	2487.62	1.83	8.37	8.45	11.06	0.20	91.85	0.41
3	-4.95	-3.83	1.13	-0.01	1.42	0.32	45.69	3039.12	1.76	8.86	7.91	10.14	0.18	90.96	0.38
4	-2.47	-1.71	1.10	-0.34	1.32	0.26	45.78	3399.11	1.78	9.22	7.60	9.58	0.17	90.31	0.36
5	-0.32	0.17	1.09	-0.60	1.17	0.14	42.75	3569.05	1.71	9.35	7.51	9.43	0.17	89.60	0.36
6	1.81	1.98	1.07	-0.90	1.01	-0.02	45.50	3649.16	1.68	9.52	7.54	9.59	0.16	89.32	0.35
7	4.12	3.94	1.07	-1.24	0.93	-0.05	49.72	3643.00	1.67	9.44	7.69	9.85	0.16	89.96	0.35
8	6.94	6.33	1.08	-1.69	0.71	-0.28	39.31	3288.98	1.70	9.06	8.07	10.66	0.16	91.27	0.36
9	11.17	9.56	1.10	-2.72	0.60	-0.38	39.56	2672.16	1.69	8.45	8.74	11.84	0.18	91.95	0.38
10	24.57	16.75	1.17	-8.99	0.34	-0.67	38.35	1598.66	1.63	6.86	10.80	15.52	0.23	90.76	0.43

Table 6

Time-series regressions: Full sample. Explanatory variables are the Fama-French three factors, lagged detrended amihud measure (amihud), lagged realized volatility on the S&P 500 index (rv), lagged numbers of IPOs (nipo), lagged net share issuance variable (s). The dependent variable is the Fama-French short-term reversal factor (Panel A), the benchmark residual-based reversal profit, and the excess returns from buying losers and selling winners for the benchmark residual-based reversal strategy (Panels C and D). The monthly Fama-French three factors and short-run reversal factor are downloaded from French's website. The detrended amihud is constructed from the difference between the Amihud (2002) illiquidity and its moving average in the previous 12 months. The realized volatility of the S&P 500 index is calculated as the annualized realized return standard deviation within a month. The nipo is the monthly number of initial public offerings, and the s is the monthly equity share in new issues, defined as the share of equity issues in total equity and debt issues. Both nipo and s are the same as in Baker and Wurgler (2006). The benchmark residual-based reversal strategy sorts stocks into deciles within each industry according to prior-month residual returns, and buys losers / sells winners within each industry. The sample period is from January 1982 through March 2009. The t-statistics reported in parentheses are Newey and West (1987) adjusted with twelve lags.

Intercept	mkt-r_f	smb	hml	lag_amihud	lag_rv	lag_nipo	lag_s
Panel A: Fama-French short-term reversal							
0.22%	0.2591	0.0769	0.1474	0.3716			
(1.22)	(4.59)	(0.67)	(1.28)	(3.52)			
-0.16%	0.2555	0.0650	0.1250		0.0158		
(-0.47)	(5.02)	(0.58)	(1.11)		(0.94)		
0.54%	0.2121	0.0321	0.0738			-0.0001	
(1.77)	(4.43)	(0.29)	(0.61)			(-1.30)	
0.58%	0.1942	0.0362	0.0558				-0.0213
(1.44)	(3.98)	(0.33)	(0.46)				(-0.78)
Panel B: Within industry residual-based reversal							
1.61%	0.2401	-0.0183	0.1093	0.3414			
(8.32)	(4.45)	(-0.16)	(1.38)	(3.28)			
1.02%	0.2578	-0.0126	0.1226		0.0286		
(2.99)	(4.59)	(-0.11)	(1.44)		(2.02)		
1.58%	0.2236	-0.0195	0.0854			0.00002	
(4.40)	(3.77)	(-0.17)	(0.91)			(0.40)	
1.48%	0.2108	-0.0278	0.0671				0.0150
(3.75)	(3.52)	(-0.24)	(0.71)				(0.83)
Panel C: Within industry residual-based reversal (buying losers)							
0.72%	1.2285	0.6371	0.3758	0.3889			
(4.76)	(27.46)	(4.33)	(3.79)	(5.18)			
0.02%	1.2611	0.6367	0.3980		0.0303		
(0.09)	(25.59)	(4.47)	(3.74)		(2.51)		
0.93%	1.2443	0.6253	0.3869			-0.0001	
(3.14)	(23.37)	(4.48)	(3.43)			(-1.49)	
0.94%	1.2341	0.6381	0.3832				-0.0170
(3.09)	(22.72)	(4.55)	(3.35)				(-1.23)
Panel D: Within industry residual-based reversal (selling winners)							
0.89%	-0.9884	-0.6554	-0.2665	-0.0476			
(8.07)	(-34.62)	(-12.37)	(-3.91)	(-0.68)			
0.99%	-1.0033	-0.6493	-0.2754		-0.0017		
(5.16)	(-37.22)	(-12.73)	(-3.86)		(-0.23)		
0.65%	-1.0207	-0.6449	-0.3015			0.0001	
(3.84)	(-38.57)	(-12.89)	(-4.47)			(3.02)	
0.54%	-1.0233	-0.6660	-0.3161				0.0320
(3.45)	(-38.37)	(-13.37)	(-4.80)				(4.01)

Table 7

Time-series regressions: Subsamples. Explanatory variables are the Fama-French three factors, lagged detrended amihud measure (amihud), lagged realized volatility on the S&P 500 index (rv), lagged numbers of IPOs (nipo), lagged net share issuance variable (s). The dependent variable are the excess returns from buying losers and selling winners for the benchmark residual-based reversal strategy within each subsample. As in Table 3, these subsamples are composed of the top 30% and bottom 30% stocks, sorted by size, book-to-market ratio, Amihud (2002) illiquidity measure, analyst forecast dispersion, and analyst coverage. Only coefficients and t-statistics on the four liquidity and sentiment variables are reported. The sample period is from January 1982 through March 2009. The t-statistics reported in parentheses are Newey and West (1987) adjusted with twelve lags.

	residual Long Excess Return				residual Short Excess Return			
Subsample	lag_amihud	lag_rv	lag_nipo	lag_s	lag_amihud	lag_rv	lag_nipo	lag_s
Small	0.5578	0.0378	-0.00017	-0.0374	-0.0603	0.0179	0.00014	0.0336
	(5.31)	(2.36)	(-2.25)	(-1.57)	(-0.51)	(1.58)	(2.30)	(2.17)
Large	0.1783	0.0150	0.00000	0.0062	-0.0574	-0.0129	0.00007	0.0249
	(2.97)	(2.22)	(-0.09)	(0.93)	(-0.76)	(-1.68)	(1.87)	(2.26)
Value	0.4193	0.0322	-0.00007	-0.0145	-0.1609	0.0105	0.00011	0.0234
	(4.39)	(2.03)	(-1.02)	(-0.79)	(-1.74)	(1.62)	(2.03)	(1.55)
Growth	0.2590	0.0219	-0.00011	-0.0045	0.1716	-0.0059	0.00009	0.0276
	(2.22)	(2.21)	(-2.73)	(-0.35)	(1.54)	(-0.58)	(1.70)	(2.04)
Illiquid	0.4373	0.0240	-0.00011	-0.0362	-0.0408	0.0254	0.00017	0.0392
	(4.53)	(1.61)	(-1.44)	(-1.74)	(-0.36)	(3.10)	(2.63)	(2.36)
Liquid	0.2412	0.0189	0.00000	0.0059	-0.0721	-0.0089	0.00003	0.0223
	(3.62)	(2.07)	(-0.10)	(0.75)	(-0.77)	(-1.29)	(0.88)	(1.52)
Low Dispersion	0.3247	0.0342	-0.00011	-0.0034	-0.2730	0.0031	0.00013	0.0256
	(2.25)	(2.34)	(-1.72)	(-0.19)	(-3.42)	(0.28)	(2.66)	(1.99)
High Dispersion	0.4457	0.0551	-0.00013	-0.0406	0.0106	0.0054	0.00001	0.0374
	(4.36)	(3.80)	(-2.39)	(-3.21)	(0.08)	(0.27)	(0.19)	(2.07)
Low Coverage	0.3849	0.0180	-0.00012	-0.0357	-0.0282	0.0083	0.00007	0.0317
	(3.29)	(0.97)	(-1.69)	(-1.66)	(-0.29)	(0.96)	(1.30)	(2.31)
High Coverage	0.2225	0.0350	-0.00004	0.0042	-0.1523	-0.0155	0.00008	0.0150
	(2.77)	(2.87)	(-0.82)	(0.44)	(-2.11)	(-1.43)	(2.20)	(1.17)

Table 8

Fama-MacBeth cross-sectional regressions: Subsamples. The dependent variable is stock return in the next month. Among the independent variables, residual denotes the residual return in previous month. The CAPM beta (beta) is estimated from the market model using monthly returns over the previous five-year rolling window (at least 36 monthly returns required). Size is market capitalization; BM is the book-to-market ratio; and turnover is the ratio between trading volume and shares outstanding, all measured in the previous month. The regressions are run separately for past losers and past winners. Past losers (winners) are those stocks with previous-month residual returns in the bottom (top) 30%. In Panel A, amihud_low (amihud_high) is a dummy variable equals to 1 if the stock's Amihud (2002) illiquidity measure is below (above) median. In Panel B, no_option is a dummy variable equal to 1 if there is no option traded on the stock, and option is another dummy variable defined as 1-no_option. All t-statistics are Newey and West (1987) adjusted with twelve lags.

Panel A: Role of illiquidity

Subsample	Intercept	residual*amihud_low (A)	residual*amihud_high (B)	beta	log(size)	log(BM)	turnover	slope difference (A-B)
past losers	1.39%	-0.0453	-0.0615	-0.1281	-0.0137	0.0007	-0.0191	0.0163
	(3.10)	(-5.79)	(-7.87)	(-0.70)	(-0.28)	(0.01)	(-3.96)	(2.44)
past winners	0.73%	-0.0286	-0.0306	-0.0607	0.0190	0.0028	0.0133	0.0020
	(1.76)	(-4.12)	(-5.54)	(-0.35)	(0.43)	(0.04)	(2.62)	(0.16)

Panel B: Role of short-sale constraints

Subsample	Intercept	residual*option_no (A)	residual*option_yes (B)	beta	log(size)	log(BM)	turnover	slope difference (A-B)
past losers	1.70%	-0.0407	-0.0221	-0.1141	-0.0441	-0.0095	-0.0208	-0.0186
	(3.78)	(-6.26)	(-3.60)	(-0.62)	(-0.98)	(-0.15)	(-4.38)	(-3.08)
past winners	0.69%	-0.0203	-0.0016	-0.1125	0.0184	0.0015	0.0113	-0.0187
	(1.71)	(-5.40)	(-0.50)	(-0.64)	(0.41)	(0.02)	(2.19)	(-4.53)