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Abstract

The profit to a standard short-term return reversal strategy can be decomposed analytically into four components: 1) across-industry return momentum, 2) within-industry variation in expected returns, 3) under-reaction to within-industry cash flow news, and 4) a residual. Only the residual component, which isolates reaction to recent "nonfundamental" price changes, is significant and positive in the data. A simple short-term return reversal trading strategy designed to capture the residual component generates a highly significant risk-adjusted return three times the size of the standard reversal strategy during our 1982-2009 sampling period. Our decomposition suggests that short-term return reversal is pervasive, much greater than previously documented, and driven by investor sentiment on the short side and liquidity shocks on the long side.

Key words: return reversal, liquidity

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1 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. 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)). Identifying the drivers of short-term reversal profits is therefore important for understanding the failings of the efficient market hypothesis of Fama (1970).

Two possible explanations for short-term reversal profits have received some 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 potential 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 (1995a). 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. 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.

We aim to advance the understanding of what is driving short-term reversal profits in the context of these competing (although not mutually exclusive) hypotheses. If reversal comes from initial price overreaction to information, to what type of information is the price overreacting? Is it industry-level news or firm-specific news? Is it news about a firm's cash flow? If, on the other hand, the reversal is due to liquidity shocks, has it remained economically relevant during recent years when market liquidity (by most measures) has improved greatly? Is it relevant even for the

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

larger and more liquid stocks that make up the majority of the US equity universe? Finally, do investor sentiment and liquidity shocks play different roles in driving the short-term reversal? In answering these questions we hope to contribute to a better understanding of the short-term return reversal phenomenon.

The framework for our analysis is a novel analytical decomposition of the short-term reversal profits. The reversal profit is first decomposed into an across-industry component and a within-industry component. The across-industry component measures the profit to an across-industry reversal strategy that buys loser industries and sells winner industries; the within-industry component measures the profit to a within-industry reversal strategy that buys losers and sells winners within each industry.

Moskowitz and Grinblatt (1999) document a strong industry momentum, in that current winner industries outperform current loser industries in the subsequent month, which implies that the across-industry reversal component will be negative on average. This suggests that the within-industry reversal component must be the source of the profits of the standard reversal strategy. Or, to put it differently: Investors overreact to firm-specific news but underreact to industry-specific news. Such stronger within-industry return reversal has been noted in Rosenberg, Reid, and Lanstein (1985) and Da and Schaumburg (2007). It is therefore of interest to further decompose the within-industry return reversal.

This second decomposition is motivated by Campbell and Shiller (1988), who decompose the stock return in any period into three components: (1) the expected return; (2) cash flow news; and (3) discount rate news. Accordingly, we decompose the within-industry return reversal into three components related to (1) within-industry variation in expected return; (2) under- or overreaction to within-industry cash flow shocks; (3) a residual component.

In the empirical implementation of our decomposition, we measure expected returns using the Fama and French (1993) three-factor model and measure the cash flow news directly using revisions of equity analyst consensus forecasts following the procedures described in Da and Warachka (2009).[2] We back out the discount rate news as the residual, or the difference between the return

[2]Similar approaches are used by Easton and Monahan (2005) and Chen and Zhao (2008). 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.

innovation (return minus an expected return measure) and the cash flow news. This means that the empirically identified discount rate component will also incorporate measurement error and deviations from fundamental value such as liquidity shocks or mispricing due to investor sentiment. Such deviations (which fall outside the Campbell and Shiller (1988) framework) will show up in returns but cannot be explained by changes in future cash flow expectation and therefore (by definition) will be included in the component labeled "discount rate news." In other words, "discount rate news" in our paper should be interpreted broadly as "return innovations that are not explained by cash flow news."

Our sample consists of all non-penny stocks that received sufficient analyst coverage to allow for measurement of cash flow news during the period January 1982-March 2009. Thus our sample includes a subset of relatively large and liquid stocks accounting for roughly 75% of the entire US equity market capitalization, and the results will therefore not be driven by positions in extremely small and illiquid stocks.

We confirm that the within-industry reversal strategy indeed outperforms the standard reversal strategy. While the standard reversal strategy often does not generate a significant positive profit (especially since the 1980s), the within-industry reversal strategy, which is unaffected by the strong industry momentum, always generates a significant positive profit (t-value = 5.49), 1.5 times the profit of a standard reversal strategy.

Further decomposing the within-industry reversal strategy into its three components reveals several interesting patterns. First, the component related to within-industry variation in expected returns is on average negative, but its size is negligible compared to the magnitude of the total reversal profit.

Second, the component related to under- or overreaction to within-industry cash flow shocks is significantly negative (t-value = -8.22), indicating that stock prices on average strongly underreact to cash flow news. It represents (in absolute terms) about 89% of the total reversal profit. Finding that prices underreact to cash flow news is of course not surprising, given the well-documented earnings momentum documented in Chan, Jegadeesh, and Lakonishok (1996).

Finally, only the residual component is large and significantly positive (t-value = 9.32), about 2.5 times the amount of the total reversal profit. We demonstrate that our decomposition result is robust to various industry classifications, choice of subsample period, and the exclusion of January months. The decomposition result also holds within each individual industry and across various subsamples constructed according to stock characteristics such as size, book-to-market, analyst coverage, analyst forecast dispersion, and liquidity. The residual component drives the short-term return reversal profit in every single robustness check we conduct. It is positive and significant even among the largest and most liquid stocks in our sample.[3]

We confirm the decomposition results using the more common portfolio-based trading strategies similar to those considered in Jegadeesh (1990). A *standard short-term reversal strategy* is a zero-investment strategy that each month sorts stocks into deciles on the basis of prior-month returns, and then buys stocks in the bottom decile (losers) and sells stocks in the top decile (winners). The standard reversal strategy generates a three-factor alpha of 0.33% per month in our sample with an insignificant t-value of 1.37. We also consider a *modified short-term reversal strategy* that sorts stocks into deciles within each industry on the basis of prior-month discount rate news (DR), the alpha further increases to 1.34% per month with a highly significant t-value of 9.28. The alpha is also economically significant, considering that a conservative spread-based estimate of transaction costs is only 0.80% per month.

The success of the DR-based reversal strategy survives a battery of robustness checks. First, it is not driven by the fact that we use I/B/E/S-month (from consensus forecast issuance date this month to consensus forecast issuance date next month). Implementing the strategy in a calendar month generates an even higher three-factor alpha of 1.63% per month (t-value = 10.29). Second, using midquote-computed returns delivers similar results so our findings are not driven unduly by bid-ask bounce. Third, the result is robust to our definition of discount rate news. In fact, a simple way to identify stocks that experienced large discount rate shocks is to look for stocks whose prices and earnings forecasts are revised in opposite directions during the prior month. Along these lines, a simple 3 by 3 within-industry double-sort, first based on prior-month stock returns and then on prior-month earnings forecast revisions generates a higher three-factor alpha of 1.72% per month (t-value = 12.24). Finally, cross-sectional regressions at individual stock level confirm our results.

The finding that short-term return reversal is driven by firm-specific discount rate news is not surprising since our "discount rate news" by construction better isolates return innovations that are

[3]We also implement an alternative decomposition proposed by Jegadeesh and Titman (1995b), and confirm that a delayed reaction to common factors is not driving the standard reversal profit in our sample.

not explained by changes in fundamental cash flow news which are more likely to revert in the near future, under both sentiment- and liquidity-based explanations. More importantly, by focusing on this "true" driver of short-term reversal, we have a new, arguably superior testing ground for different explanations of short-term reversal. Additional regression results suggest that liquidity shock is more likely to affect recent losers while investor sentiment is more likely to affect recent winners.

We find the profits from buying losers (the long-side in the DR-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 notion that it is easier to provide liquidity as a buyer (since you need to own the stock first in order to provide liquidity as a seller). Nagel (2011) also relates short-term return reversal to liquidity provision. Our novel decomposition allows us to extend Nagel's (2011) analysis by showing that liquidity provision appears more important for explaining the reversal on recent losers.

In contrast, we find the profits from selling winners (the short-side in the DR-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. Both are used by Baker and Wurgler (2006) in constructing their investor sentiment index.[4] Hirshleifer and Jiang (2010) also consider security issuance as a proxy for aggregate overvaluation. 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. Again, by isolating recent "non-fundamental" price change, our decomposition shows that Miller's argument also extends to the short-term return reversal, even among large stocks.

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

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

Overall, the key message in our paper can be summarized as that short-term return reversal is pervasive, much higher than previously documented, attributable to liquidity shocks on the long side and investor sentiment on the short side. Our finding is of general interest to asset pricing researchers, as recent studies by Da and Gao (2008) and Huang, Liu, Rhee, and Zhang (2010) among others document short-term reversals to have important implications for empirical asset pricing tests. Our decomposition framework is also quite general and can be applied to analyze other return-based anomalies such as medium-term return momentum (Jegadeesh and Titman (1993)) and long-run return reversal (De Bondt and Thaler (1985)).

The rest of the paper is organized as follows. Section 2 describes our analytical reversal decomposition framework in details. Section 3 discusses its empirical implementation and describes our sample. Section 4 contains the empirical decomposition results. Section 5 considers various portfolio-based trading strategies. Section 6 discusses the differential roles played by investor sentiment and liquidity shock in driving the reversal and Section 7 concludes.

2 Decomposing Short-Term Return Reversal

For simplicity, assume that there are N stocks and K industries in the economy. The number of stocks in industry j is N^j so $\sum N^j = N$. Following Lehmann (1990), Lo and MacKinlay (1990) and Jegadeesh and Titman (1995b), we consider a zero-investment portfolio strategy where the portfolio weight on stock i is:

$$w_{i,t} = -\frac{1}{N}(r_{i,t-1} - r^M_{t-1}), \quad i = 1, \ldots, N \tag{1}$$

where $r^M_{t-1} = \frac{1}{N}\sum_i r_{i,t-1}$ is the equal-weighted market return in the previous month. By construction, (1) is a contrarian strategy as it sells more past winners and buys more past losers and is indeed a zero-investment strategy since $\sum w_{i,t} = 0$.

The reversal strategy return is:

$$\pi_t = -\frac{1}{N}\sum_{i=1}^{N}(r_{i,t-1} - r_{t-1}^{M})r_{i,t} \tag{2}$$

2.1 Across-industry momentum and within-industry reversal

We first separate the within-industry component from the across-industry component in the return to the standard reversal strategy:

$$\begin{aligned}
\pi_t &= -\frac{1}{N}\sum_{i=1}^{N}(r_{i,t-1} - r_{t-1}^{j} + r_{t-1}^{j} - r_{t-1}^{M})r_{i,t} \qquad (3)\\
&= -\frac{1}{N}\sum_{j=1}^{K}N^j\frac{1}{N^j}\sum_{i=1}^{N^j}(r_{i,t-1} - r_{t-1}^{j})r_{i,t} - \frac{1}{N}\sum_{j=1}^{K}N^j(r_{t-1}^{j} - r_{t-1}^{M})\frac{1}{N^j}\sum_{i=1}^{N^j}r_{i,t}\\
&= \frac{1}{N}\sum_{j=1}^{K}N^j\pi_t^j + \Omega_{m,t},
\end{aligned}$$

where we define the cross-sectional average return in industry j in period $t-1$, r_{t-1}^{j}, and

$$\pi_t^j = -\frac{1}{N^j}\sum_{i=1}^{N^j}(r_{i,t-1} - r_{t-1}^{j})r_{i,t}, \; j = 1, \ldots, K \tag{4}$$

$$\Omega_{m,t} = -\frac{1}{N}\sum_{j=1}^{K}N^j(r_{t-1}^{j} - r_{t-1}^{M})r_t^j \tag{5}$$

Clearly π_t^j can be interpreted as the profit to a within-industry reversal strategy. The standard reversal profit has two parts. The first term represents the weighted-average of K within-industry reversal strategies (buying losers and selling winners within each industry) weighted by number of stocks in each industry. The second term $\Omega_{m,t}$ represents the return to an across-industry reversal strategy (buying loser industries and selling winner industries) weighted by the number of stocks in each industry.

Moskowitz and Grinblatt (1999) document a strong industry momentum in which winner industries outperform loser industries in the subsequent month. As a result, the second term $\Omega_{m,t}$ will be negative on average, which in turn suggests that the within-industry reversal strategy will outperform the standard reversal strategy as noted in Rosenberg, Reid, and Lanstein (1985) and Da and Schaumburg (2007). In other words, the presence of industry momentum reduces the overall profitability of the standard return reversal strategy.

2.2 Decomposing within-industry reversal

Jegadeesh and Titman (1995b) find that most of the short-term reversal profit is due to stock price overreaction to firm-specific information. But to which kind of firm-specific news are stock prices overreacting? To address this question, we further decompose the within-industry reversal profit using the framework of Campbell and Shiller (1988) and Campbell (1991) who show that the realized return on stock i in period $t+1$ can be decomposed into three components: the expected return (μ), the cash flow news (CF), and the discount rate news (DR):

$$r_{i,t+1} = \mu_{i,t} + CF_{i,t+1} + DR_{i,t+1} \tag{6}$$

where

$$\begin{aligned} \mu_{i,t} &= E_t\left[r_{i,t+1}\right] \\ CF_{i,t+1} &= \left(E_{t+1} - E_t\right)\sum_{j=0}^{\infty}\rho^j \Delta d_{i,t+j+1}, \\ DR_{i,t+1} &= -\left(E_{t+1} - E_t\right)\sum_{j=1}^{\infty}\rho^j r_{i,t+j+1}. \end{aligned}$$

Δd denotes dividend growth and ρ is a log-linearization constant which is often set to 0.96 at an annual horizon.

The same decomposition can be applied to the return on industry j:

$$r^j_{t+1} = \overline{\mu}^j_t + \overline{CF}^j_{t+1} + \overline{DR}^j_{t+1}.$$

which allows us to write the within-industry reversal profit as

$$\pi^j_t = -\frac{1}{N^j}\sum_{i=1}^{N^j}(\mu_{i,t-2} - \overline{\mu}^j_{t-2} + \widetilde{CF}_{i,t-1} + \widetilde{DR}_{i,t-1})r_{i,t},$$

where $\widetilde{CF}$ and $\widetilde{DR}$ measure industry-demeaned cash flow or discount rate news, and are thus more likely capturing firm-specific news. π_t^j can be decomposed into three components as follows:

$$\begin{aligned} \pi_t^j &= \Omega_{\mu,t}^j + \Omega_{CF,t}^j + \Omega_{DR,t}^j \\ \Omega_{\mu,t}^j &= -\frac{1}{N^j}\sum_{i=1}^{N^j}(\mu_{i,t-2} - \overline{\mu}_{t-2}^j)r_{i,t} \\ \Omega_{CF,t}^j &= -\frac{1}{N^j}\sum_{i=1}^{N^j}\widetilde{CF}_{i,t-1}r_{i,t} \\ \Omega_{DR,t}^j &= -\frac{1}{N^j}\sum_{i=1}^{N^j}\widetilde{DR}_{i,t-1}r_{i,t}. \end{aligned} \tag{7}$$

The first term, Ω_μ^j, captures the cross-sectional variance of expected returns, μ, in industry j. The second term, Ω_{CF}^j, captures the (cross-sectional) average covariance between the current return on a stock in industry j and its previous-month firm-specific cash flow shock.[5] It therefore is a measure of the average under- or overreaction to cash flow shocks in that industry. Analogously, the third term, Ω_{DR}^j, is the (cross-sectional) average covariance between the current return on stock i in industry j and the previous-month firm-specific discount rate shock and captures the effect of under- or overreaction to discount rate shocks.

Interestingly, all three components can be interpreted as profits to zero-investment strategies. This is because $-\frac{1}{N^j}(\mu_{i,t-2} - \overline{\mu}_{t-2}^j)$, $-\frac{1}{N^j}\widetilde{CF}_{i,t-1}$, and $-\frac{1}{N^j}\widetilde{DR}_{i,t-1}$ can all be viewed as portfolio weights that add up to zero over the N^j stocks in each industry.

The return to a standard reversal strategy thus has four components related to (1) across-industry return momentum ($\Omega_{m,t}$); (2) within-industry variation in expected return ($\Omega_{\mu,t}$); (3) under- or overreaction to within-industry cash flow shocks ($\Omega_{CF,t}$); and (4) under- or overreaction

[5] "Firm-specific" is here taken to mean in excess of the industry average cash flow shock.

to within-industry non-cash-flow shocks ($\Omega_{DR,t}$). The equations are:

$$
\begin{aligned}
\pi_t &= \Omega_{m,t} + \Omega_{\mu,t} + \Omega_{CF,t} + \Omega_{DR,t}, \\
\Omega_{m,t} &= -\frac{1}{N}\sum_{j=1}^{K} N^j (r^j_{t-1} - r^M_{t-1}) r^j_t, \\
\Omega_{\mu,t} &= \frac{1}{N}\sum_{j=1}^{K} N^j \Omega^j_{\mu,t}, \\
\Omega_{CF,t} &= \frac{1}{N}\sum_{j=1}^{K} N^j \Omega^j_{CF,t}, \\
\Omega_{DR,t} &= \frac{1}{N}\sum_{j=1}^{K} N^j \Omega^j_{DR,t}.
\end{aligned} \tag{8}
$$

Our decomposition holds as an identity both period-by-period and on average. We effectively decompose the standard zero-investment reversal strategy into four different zero-investment trading strategies, each with a distinct economic interpretation.

2.3 Scaling adjustment

The zero-investment trading strategies we have considered so far, which originated from Lehmann (1990), have one shortcoming: the dollar investment amounts on the long or short side are changing each month so the resulting profits cannot be interpreted as percentage returns. To fix this problem, we now scale the investment on both long and short sides to be \$1, this can be easily achieved by applying the following scaling factor (M_t) to the portfolio weight for all zero-investment trading strategies:

$$
\begin{aligned}
w^\star_{i,t} &= \frac{w_{i,t}}{M_t}, \\
M_t &= \frac{1}{2}\sum_{i=1}^{N} |w_{i,t}| .
\end{aligned} \tag{9}
$$

After this scaling adjustment, all profits have the usual (excess) return interpretations.

3 Empirical Measurement

The decomposition (8) requires the measurement of expected returns ($\mu_{i,t+1}$), cash flow shocks ($CF_{i,t+1}$), and discount rate shocks ($DR_{i,t+1}$). Once the different components are constructed, the short-term return reversal in equation (8) can easily be implemented.

3.1 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:

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

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.

3.2 Cash flow shocks

A popular way to implement Campbell and Shiller's (1988) return decomposition in equation (6) is to use a vector autoregression (VAR). Campbell and Vuolteenaho (2004) implement a VAR at the market level, while Campbell, Polk, and Vuolteenaho (2010) implement it at the firm level. The VAR approach is economically appealing and allows for time-varying discount rates. Empirically, however, Chen and Zhao (2009) argue that the VAR approach might be sensitive to the choices of state variables. In addition, accounting variables that are required to implement the VAR at firm level are updated quarterly at best.

Instead, 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.[6]

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.

We first define a simple proxy for the cash flow innovation using only revisions in the earnings forecast for the current fiscal year ($A1_t$):[7]

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

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

[6]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.

[7]For notional simplicity, we omit the firm-i subscript.

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:[8]

$$\begin{aligned} X_{t,t+1} &= A1_t, \\ X_{t,t+2} &= A2_t, \\ X_{t,t+3} &= A2_t\,(1+LTG_t), \\ X_{t,t+4} &= X_{t,t+3}\,(1+LTG_t), \\ X_{t,t+5} &= X_{t,t+4}\,(1+LTG_t). \end{aligned} \tag{10}$$

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.

Expected earnings in the second stage are estimated as:

$$X_{t,t+j+1} = X_{t,t+j}\left[1+LTG_t+\frac{j-4}{5}\,(g_t-LTG_t)\right], \tag{11}$$

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

[8] 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.

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:[9]

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

where the $X_{t,t+j+1}$ expectations are defined in equations (10) and (11).

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:[10]

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

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.

3.3 Discount rate shocks

Since we do not have an empirically observable direct measure of discount rate news, we *define* the discount rate news as the residual:

$$DR_{t+1} = r_{t+1} - \mu_t - CF_{t+1}. \tag{12}$$

As the discount rate news are backed out, we want to emphasize that they are really residuals and should be better interpreted as "non-cash-flow news." Any unexpected stock returns that are

[9] 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.

[10] 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.

not explained by the cash flow news will be contained in our discount rate news component. For example, liquidity shocks may cause price impact that are not justified by cash flow news. Another example is mispricing due to investor sentiment. In fact, investor sentiment, according to Baker and Wurgler (2007), is broadly defined as "a belief about future cash flows and investment risks that is not justified by the facts at hand." Finally, to the extent that cash flow news may be measured with error, the same error will show up in our discount rate news (with the opposite sign). For such measurement error to contribute to the reversal profit, however, it needs to have strong predictive power about next-month return which is unlikely.

3.4 Sample description

Our final sample consists of stock / month observations where the expected return, cash flow news, and discount rate 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.

4 Empirical Decomposition Results

Table 2 reports the results of the short-term return reversal decomposition (8). During the period 1982-2009, the total reversal profit (π) is 0.526% per month with a t-value of 2.66 as shown in

Panel A. The across-industry component, stemming from selling winner industries and buying loser industries, (Ω_m) is -0.295% with a t-value of -4.15, confirming the strong industry momentum effect documented yb Moskowitz and Grinblatt (1999). As a result, the within-industry component, or the difference between π and Ω_m, is larger, at 0.821% and a t-value of 5.49.

In other words, the industry momentum effect means that implementing the short-term reversal strategy within an industry is more profitable than implementing it across the board. One interpretation of this result is that investors tend to overreact to firm-specific news but underreact to industry-level news.

When we further decompose the within-industry component, several patterns emerge. First, the component related to within-industry variation in expected return (Ω_μ) is negative but small (-0.002% with a t-value of -0.34).

Second, the component related to within-industry cash flow shock (Ω_{CF}) is negative and large (-0.469% with a t-value of -8.22). The negative Ω_{CF} suggests that a positive (negative) within-industry cash flow shock this month tends to be followed by a higher (lower) return next month, or return underreacts to cash flow shocks measured using earnings revisions. This pattern is consistent with the earnings momentum documented by Chan, Jegadeesh, and Lakonishok (1996) and the post-earnings announcement drift (PEAD) documented by Ball and Brown (1968) and Bernard and Thomas (1989).

Finally, the component related to within-industry non-cash-flow shock (Ω_{DR}), as the only positive component, is large and hugely significant (1.292% with a t-value of 9.32). The positive Ω_{DR}, which reflects overreaction to within-industry non-cash-flow news, clearly drives the overall profit to the standard reversal strategy. It is almost 2.5 times the size of the standard reversal profit.

Figure 1 provides a graphic representation of these results. Of the four components, Ω_{DR} is higher and more volatile, and clearly drives both the level and the variation of the total reversal profits (π).

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 the decomposition results after removing January from the sample. The total reversal profit (π) becomes smaller and less significant (0.365% with a t-value of 1.79). After removing the industry momentum effect, the within-industry component is larger and significant (0.669% with a t-value of 4.36). Finally, Ω_{DR} is still the only large and positive component (1.185% with a t-value of 8.29).

Panel B of Table 2 reports the decomposition results across three subsample periods: 1982-1989, 1990-1999, and 2000-2009. We find very similar decomposition patterns over time although the total reversal profit becomes smaller and insignificant after the 1980s. The within-industry component is larger than the total reversal profit and more significant in all three periods. The component related to overreaction to within-industry non-cash-flow news (Ω_{DR}) is again the largest and the most significant.

Panel C confirms the robustness of our decomposition results to alternative industry classifications. When we use the Fama-French 17 or 48 industry classifications, we obtain almost identical decomposition results.

4.1 Subsample results

Results for decomposition in various subsamples are reported in Table 3. We examine whether the decomposition 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, analyst coverage, analyst forecast dispersion, and the Amihud (2002) illiquidity measure. We then implement our reversal decomposition in each group. To save space, we report the results for only top and bottom groups.

We first note that the sign and relative size of each component (of the total reversal profit) are similar across extreme groups of stocks. Ω_μ is relatively small and insignificant. Ω_m and Ω_{CF} are always negative and significant. Ω_{DR} is always the largest and the most significant component, representing on average 2.5 times the standard reversal profit. Unreported results suggest that the decomposition pattern is also very similar across industries.

Across extreme groups of stocks sorted on size, liquidity and analyst coverage, we find both the standard reversal profit (π) and its discount rate component (Ω_{DR}) are higher among smaller stocks, illiquid stocks, and stocks covered by fewer analysts. In fact, the standard reversal profit is significant only in these groups. The discount rate overreaction component (Ω_{DR}), on the other hand, is significantly positive in all groups.

So far, we have shown that the standard short-term reversal profit is driven by overreaction to firm-specific non-cash-flow shocks. Using an alternative decomposition framework, Lo and MacKinlay (1990) raise the possibility that delayed reactions to common return factors are driving short-term return reversals. Jegadeesh and Titman (1995b) refine the Lo and MacKinlay decomposition framework, and find that most of the reversal profit is due to stock price overreaction, and only a very small fraction of the profit can be attributed to a delayed reaction to common factors. As our stock sample is quite different from that used in Jegadeesh and Titman (1995b) in terms of both sample period and stock characteristics, we repeat this decomposition within each industry and confirm that delayed reactions to common return factors are not driving the standard reversals in our sample. To save space, we do not report these results but they are available upon request.

5 Portfolio-Based Trading Strategy Results

We have shown how to decompose the standard reversal strategy of Lehmann (1990), Lo and MacKinlay (1990), and Jegadeesh and Titman (1995b) into four distinct zero-investment trading strategies. Our results demonstrate that the reversal profit is driven mainly by the component that captures overreaction to firm-specific non-cash-flow shocks. We can also confirm the robustness of this key result using the alternative portfolio-based trading strategy considered in Jegadeesh (1990).

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 4.

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.

Our analytical decomposition suggests that the standard short-term reversal strategy is adversely affected by the industry momentum effect. As a result, a within-industry reversal strategy should perform better. This is indeed the case as reported in Panel B of Table 4. 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.

Our decomposition results have also suggested that stock prices react differentially to different types of firm-specific information. That is, investors on average appear to underreact to cash flow news but overreact to discount rate news. Hence a within-industry reversal strategy based on past discount rate news should perform even better. To test this, we sort stocks into deciles within each industry by prior-month discount rate news (DR). We then buy stocks in the bottom decile (with the most negative DR) and sell stocks in the top decile (with the most positive DR). We label this modified reversal strategy our *benchmark* DR*-based reversal strategy.*

The benchmark DR-based reversal strategy indeed performs the best, as reported in Panel C of Table 4. 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 DR-based reversal strategy and the standard reversal strategy is provided in Figure 2. 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 DR-based reversal strategy clearly dominates; its return series are both higher on average and much less volatile. As a result, our benchmark DR-based reversal strategy has a much higher Sharpe ratio. For raw returns, the monthly Sharpe ratio is 0.52 for the benchmark DR-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 DR-based reversal strategy and only 0.08 for the standard reversal strategy.

5.1 Subsample and robustness results

Panel A of Table 5 shows the performance of the benchmark DR-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 discount rate news 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 DR-based reversal strategy, the profit actually improves as reported in Panel B of Table 5. 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 5, show that the DR-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.

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 discount rate shocks: 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 be due to a large discount rate (or liquidity) shock realization.

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 5. 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 DR strategy and the parametric DR strategy is very high ($\rho = 0.76$) as is its correlation with Ω_{DR} ($\rho = 0.80$), consistent with a conclusion that the alternative strategies capture similar effects of discount rate shocks.

Finally, unreported results suggest that the benchmark DR-based reversal strategy generates significantly positive profit in each of the 11 industries, with t-values ranging from 3.81 to 6.45.

Overall, the superior performance of the benchmark DR-based reversal strategy once again confirms within-industry discount rate news to be the main driver of short-term return reversal. By isolating the main driver, the benchmark DR-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 DR-based reversal strategy.

5.2 Portfolio characteristics and cross-sectional regressions

Table 6 reports average portfolio characteristics across the decile portfolios sorted on within-industry non-cash-flow shock (DR). Stocks in portfolio 1 on average experienced a large negative discount rate shock (DR = -18.07%) during the formation month (0). The negative discount rate shock 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 discount rate shock (DR = 24.57%) during the formation month (0). The positive discount rate shock 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 4, Panel C), portfolio 1 outperforms portfolio 10 during the first month after portfolio formation. As seen in Table 6, both raw returns and the three-factor alphas decline monotonically in within-industry non-cash-flow shock (DR), suggesting that DR 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 overreaction.

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 discount rate shocks nor liquidity shocks are expected to persist.[11] 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 DR-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 6 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.

Finally, Table 7 confirms the importance of short-term overreaction to non-cash-flow news in a cross-sectional regression framework. In a Fama-MacBeth (1973) cross-sectional regression, we regress the monthly individual stock return on prior-month return, its components, and other stock characteristics. We compute the t-values using the Newey-West (1987) formula to account for autocorrelation and heteroskedasticity in the error terms.

The coefficient on return in the previous month is significantly negative, which indicates short-term return reversals. The industry-demeaned return has a negative coefficient with a larger t-statistic (in absolute terms) than that of the prior-month return. The within-industry cash flow news is strongly positively related to stock return in the subsequent month, indicating an earnings momentum effect.

The regression results suggest that within-industry non-cash-flow news (DR) is consistently the strongest predictor of next-month stock return. The coefficients are negative, and t-values are all above 7 (in absolute terms) in different models. More important, none of the coefficients on prior-month return, industry-demeaned return, or industry-demeaned cash flow revision are significant once the industry-demeaned DR is included in the regression models.

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

6 Liquidity Shock *vs.* Investor Sentiment

Our DR-based reversal strategy outperforms the standard reversal strategy since the DR 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. We 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 might also be driven by liquidity as well. Hirshleifer and Jiang (2010) also consider security issuance as a proxy for aggregate overvaluation.

The time series regression results are reported in Table 8. 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.[12] 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 DR-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 DR-based strategy separately. This separation yields very interesting results. We find the profits from buying losers or the long-side in DR-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 notion that it is easier to provide liquidity as a buyer (since you need to own the stock first in order to provide liquidity as a seller). Obizhaeva (2007), in the context of portfolio transition trades, provides a similar example. 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 DR-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 constraints 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

[12] 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 $1/2(SmallLow + BigLow) - 1/2(SmallHigh + BigHigh)$.

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 decomposition shows that Miller's argument also extends to the short-term return reversal, even among large stocks.

Figure 3 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 DR-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 9, 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 8 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.

To summarize, the 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.

7 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. We attempt to shed some new light on the sources of short-term reversal profits by proposing a novel analytical decomposition.

We show that the profit to the standard short-term return reversal strategy can be decomposed into four components related to (1) across-industry return momentum; (2) within-industry variation in expected returns; (3) under-reaction to within-industry cash flow shocks; and (4) a residual component capturing reaction to recent "non-fundamental" price changes .

Proxying for the cash flow shock using analyst earnings forecast revisions, we find that only the fourth residual component is large and positive over the 27-year period of our sample of large stocks with analyst coverage. A simple short-term return reversal trading strategy based on the previous-month within-industry non-cash-flow shock 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 on recent losers while investor sentiment is more likely to drive reversals on recent winners.

Finally, our novel decomposition framework is quite general, and can be used to analyze the drivers of other return-based anomalies such as medium-term return momentum and long-run return reversal. This should make our work be of general interest to a broad cross-section of asset pricing researchers.

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Figure 1: **Components of short-term return reversal profit.** The time series of the four components in the short-term return reversal profit decomposition. The profit is based on $1 each in long and short positions. The components, denoted Ω_m, Ω_μ, Ω_{CF}, Ω_{DR} measure cross-industry return momentum, within-industry variation in expected return, underreaction to within-industry cash flow shock, and overreaction to within-industry discount rate shock, respectively.

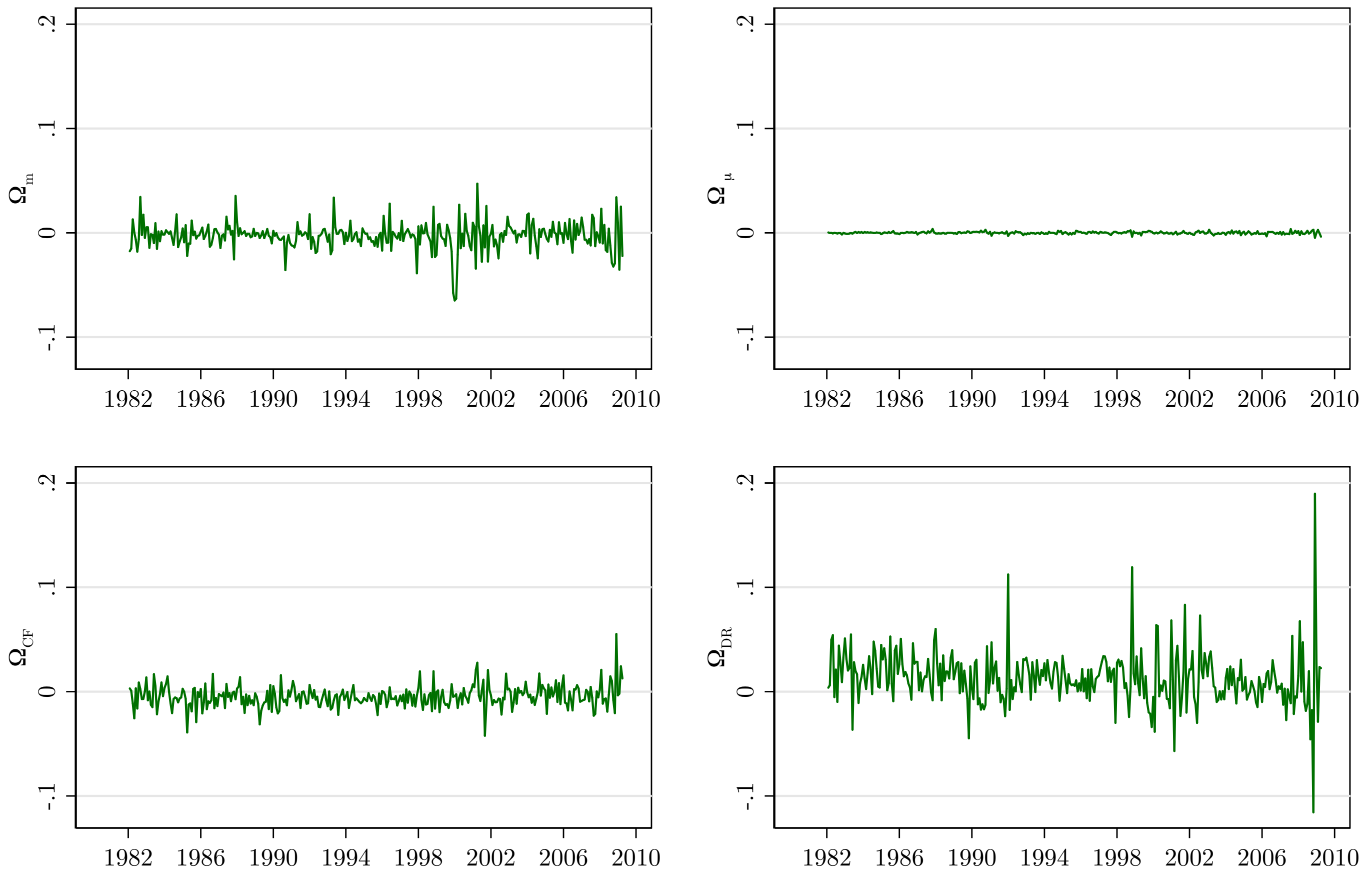

Figure 2: **Components of short-term return reversal profit.** The time series of raw returns (top panel) and Fama-French (1993) three-factor adjusted returns (bottom panel) for the standard reversal strategy (dotted) and the benchmark DR-based reversal strategy (solid).

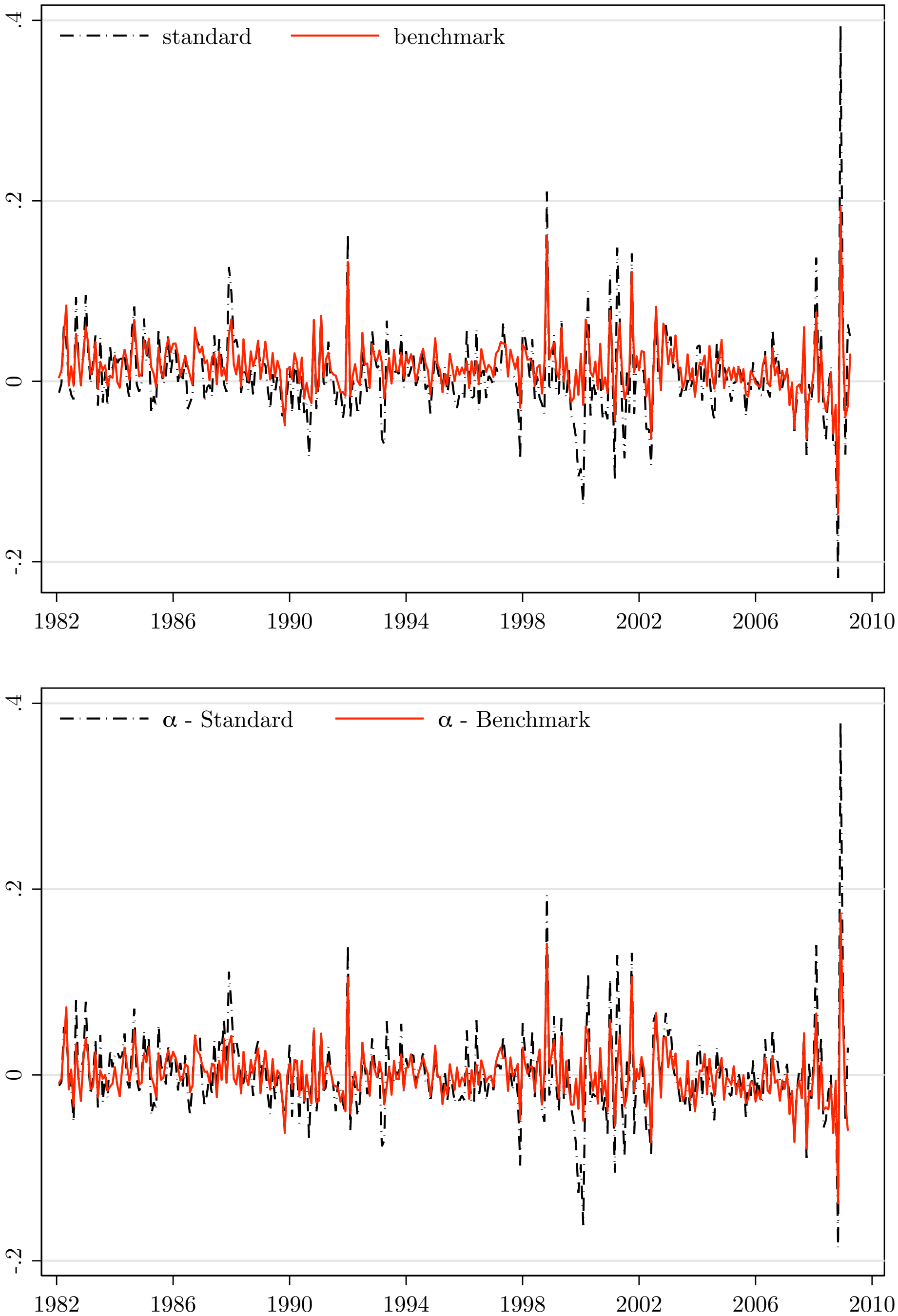

Figure 3: **Time series of Fama-French (1993) three-factor adjusted returns.** Risk adjusted returns on the long and short portfolios of the benchmark DR-based reversal strategy are plotted separately against the time series of the number of IPOs (nipo), net share issuance(s), the realized volatility 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.

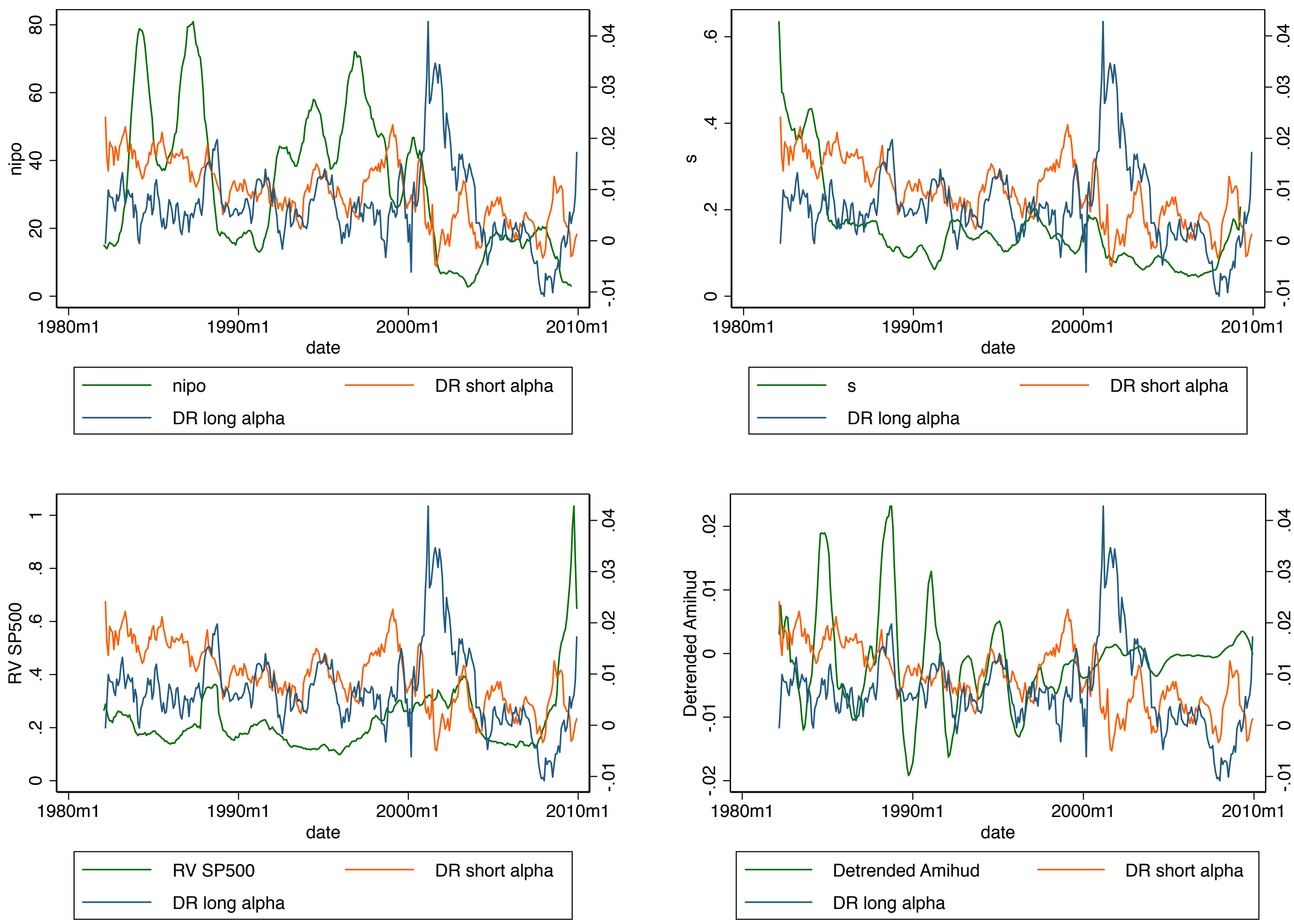

Table 1: **Characteristics of the sample.** Reported are several characteristics of the stock sample from the Institutional Brokers Estimate System (I/B/E/S) Summary unadjusted file used in our empirical analysis. The full sample period is from January 1982 through March 2009. The stock-level characteristics 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: **Decomposition of short-term return reversal profit.** π represents the profit to a standard reversal strategy per dollar long, while π^j represents the profit to a within-industry reversal strategy. Ω_m, Ω_μ, Ω_{CF}, Ω_{DR} measure across-industry return momentum, within-industry variation in expected return, underreaction to within-industry cash flow shocks, and overreaction to within-industry discount rate shocks, respectively. Panel A reports the decomposition in all months and non-January months of the full sample from January 1982 through March 2009. Panel B reports the decomposition in all months from three subsampling periods: January 1982 through December 1989, January 1990 through December 1999, and January 2000 through March 2009. Both panels are based on I/B/E/S industry classifications. Panel C reports the decomposition in all months of the full sample for the Fama-French 17 and 48 industry classifications. T-statistics are reported in parentheses.

	π	π^j	Ω_m	Ω_μ	Ω_{CF}	Ω_{DR}
Panel A: Full sample						
All months	0.53%	0.82%	-0.30%	0.00%	-0.47%	1.29%
	(2.66)	(5.49)	(-4.15)	(-0.34)	(-8.22)	(9.32)
Non-January months	0.37%	0.67%	-0.30%	0.00%	-0.52%	1.19%
	(1.79)	(4.36)	(-4.19)	(0.19)	(-8.54)	(8.29)
Panel B: Three subsampling periods						
Jan 1982 – Dec 1989	1.18%	1.32%	-0.14%	0.00%	-0.58%	1.90%
	(4.74)	(7.18)	(-1.40)	(0.26)	(-5.51)	(9.64)
Jan 1990 – Dec 1999	0.12%	0.58%	-0.47%	0.01%	-0.61%	1.19%
	(0.42)	(2.73)	(-4.04)	(0.66)	(-8.66)	(6.10)
Jan 2000 – Mar 2009	0.40%	0.65%	-0.25%	-0.02%	-0.22%	0.88%
	(0.90)	(1.92)	(-1.71)	(-1.16)	(-1.88)	(2.94)
Panel C: Alternative industry classifications						
FF17	0.53%	0.76%	-0.24%	0.00%	-0.49%	1.25%
	(2.66)	(4.90)	(-4.14)	(-0.29)	(-8.40)	(8.54)
FF48	0.53%	0.83%	-0.30%	0.00%	-0.46%	1.29%
	(2.66)	(5.84)	(-4.27)	(-0.19)	(-8.28)	(9.71)

Table 3: **Decomposition of short-term return reversal profit in subsamples.** Stocks are sorted by size, book-to-market ratio, Amihud (2002) illiquidity measure, analyst forecast dispersion, and analyst coverage. The analyst forecast dispersion is defined as the ratio of the standard deviation to the absolute value of the median of analyst earnings forecasts. The stocks are sorted into three groups by characteristic: top 30%, middle 40%, and bottom 30%. We report the decomposition for the top and bottom groups, and their differences. The sample period is from January 1982 through March 2009. T-statistics are reported in parentheses.

	π	π^j	Ω_m	Ω_μ	Ω_{CF}	Ω_{DR}
Small	0.87%	1.16%	-0.29%	0.00%	-0.72%	1.88%
	(4.22)	(6.59)	(-5.14)	(-0.04)	(-7.53)	(10.50)
Large	0.29%	0.46%	-0.17%	-0.01%	-0.20%	0.67%
	(1.35)	(3.40)	(-1.60)	(-1.42)	(-3.03)	(4.83)
Difference	0.58%	0.70%	-0.12%	0.01%	-0.52%	1.22%
	(3.50)	(5.34)	(-1.39)	(1.46)	(-4.92)	(7.66)
Value	0.72%	1.03%	-0.31%	-0.01%	-0.51%	1.54%
	(3.41)	(5.87)	(-5.19)	(-0.71)	(-6.99)	(9.08)
Growth	0.51%	0.69%	-0.18%	-0.01%	-0.40%	1.09%
	(2.36)	(4.14)	(-2.26)	(-0.63)	(-3.90)	(6.10)
Difference	0.21%	0.34%	-0.13%	0.00%	-0.11%	0.45%
	(1.06)	(2.17)	(-1.66)	(-0.10)	(-0.97)	(2.51)
Illiquid	1.31%	1.58%	-0.28%	0.00%	-0.63%	2.22%
	(7.28)	(10.17)	(-5.44)	(-0.09)	(-6.92)	(13.76)
Liquid	0.19%	0.38%	-0.19%	-0.01%	-0.24%	0.63%
	(0.80)	(2.51)	(-1.60)	(-1.47)	(-3.13)	(4.15)
Difference	1.11%	1.20%	-0.09%	0.01%	-0.39%	1.58%
	(5.89)	(9.09)	(-0.84)	(1.39)	(-3.48)	(9.92)
Low Dispersion	0.89%	1.14%	-0.25%	-0.01%	-0.24%	1.39%
	(5.36)	(9.22)	(-3.59)	(-1.17)	(-4.50)	(10.56)
High Dispersion	0.43%	0.73%	-0.29%	-0.01%	-0.84%	1.57%
	(2.11)	(4.59)	(-3.34)	(-1.14)	(-6.80)	(8.70)
Difference	0.46%	0.41%	0.04%	0.00%	0.59%	-0.18%
	(2.99)	(3.08)	(0.59)	(-0.02)	(4.58)	(-0.99)
Low Coverage	0.59%	0.87%	-0.28%	0.00%	-0.77%	1.64%
	(3.01)	(5.43)	(-4.43)	(0.21)	(-8.67)	(9.96)
High Coverage	0.37%	0.56%	-0.19%	0.00%	-0.24%	0.81%
	(1.48)	(3.38)	(-1.55)	(-0.45)	(-2.90)	(5.15)
Difference	0.22%	0.31%	-0.09%	0.01%	-0.53%	0.83%
	(1.24)	(2.40)	(-0.89)	(0.73)	(-4.58)	(5.16)

Table 4: **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 DR-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 DR-based) reversal strategy sorts stocks into deciles within each industry according to prior-month returns (discount rate news, DR), 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 DR-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 5: **Within-industry DR-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 DR-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 DR-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 6: **Characteristics of discount rate news (DR)-sorted decile portfolios.** Portfolio 1 has a large negative discount rate shock during the formation month (0), while Portfolio 10 has a large positive discount rate shock. 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 DR-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.

Portfolio	DR (%)	Ret (0) (%)	ER (%)	CF rev (%)	Ret(+1) (%)	3-factor alpha (%)	Price	Size	BM	NoA	IVOL (%)	Turnover (%)	Amihud illiquidity	Portfolio Turnover	Spread (%)
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 7: **Fama-MacBeth cross-sectional regressions.** Explanatory variables are the current-month stock return (Ret(0)), the industry-demeaned return, the industry-demeaned cash flow revision, the industry-demeaned discount rate, the CAPM beta, log(Size), and log(BM); the dependent variable is stock return in the next month (Ret(+1)). The industry-demeaned return is the difference between a stock return and the stock's average industry return. The industry-demeaned cash flow revision (discount rate) measures the difference between the cash flow (discount rate) news and its average within an industry. The CAPM 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, and BM is the book-to-market ratio in the previous month. The t-statistics are Newey and West (1987) adjusted with twelve lags.

Intercept	Ret(0)	industry-demeaned return	industry-demeaned cash flow revision	industry-demeaned discount rate	beta	log(Size)	log(BM)
1.31%					-0.0626	-0.0196	-0.0119
(3.41)					(-0.31)	(-0.48)	(-0.19)
1.33%	-0.0262				-0.0912	-0.0200	-0.0147
(3.32)	(-4.76)				(-0.46)	(-0.49)	(-0.24)
1.34%		-0.0349			-0.0836	-0.0221	-0.0186
(3.45)		(-6.92)			(-0.42)	(-0.53)	(-0.30)
1.32%			0.0244		-0.0549	-0.0231	-0.0054
(3.45)			(8.42)		(-0.28)	(-0.57)	(-0.09)
1.34%				-0.0331	-0.0676	-0.0251	-0.0155
(3.44)				(-9.97)	(-0.34)	(-0.61)	(-0.25)
1.31%	0.0077			-0.0395	-0.0935	-0.0234	-0.0075
(3.31)	(1.08)			(-11.05)	(-0.48)	(-0.57)	(-0.13)
1.36%		-0.0080		-0.0295	-0.0823	-0.0254	-0.0141
(3.50)		(-1.43)		(-11.06)	(-0.41)	(-0.61)	(-0.23)
1.36%			-0.0080	-0.0377	-0.0831	-0.0253	-0.0145
(3.50)			(-1.39)	(-7.49)	(-0.42)	(-0.61)	(-0.23)

Table 8: **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 DR-based reversal profit, and the excess returns from buying losers and selling winners for the benchmark DR-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 (2007). The benchmark DR-based reversal strategy sorts stocks into deciles within each industry according to prior-month discount rate news (DR), 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 DR-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 DR-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 DR-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 9: **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 DR-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.

	DR Long Excess Return				DR 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)