Fresh Momentum

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Abstract

We demonstrate an inconsistency of the momentum and reversal effects in explaining stock return dynamics. We argue that a two-way sorting based on long-term and recent performance can accommodate the two effects by distinguishing between fresh and stale winners and losers. Building on this idea, we propose a fresh momentum strategy which invests in fresh winners and fresh losers only. This strategy generates a fresh momentum profit of 10.2percent per year even after controlling for the Carhart four-factor model (including momentum). To explain the phenomenon, we argue that investors mistakenly respond to shocks to firm fundamentals as if they are going to continue in the long run, and these mistakes are exacerbated for fresh momentum stocks, presumably generating the abnormally large returns over the short run. This hypothesis is strongly supported by evidence from earnings shocks, analyst forecast revisions, and post-earnings announcement returns.

Keywords : *Momentum, reversal, analyst forecast, earnings,announcement returns*

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1 Introduction

In finance literature, there is extensive research on time series and cross sectional patterns in average stock returns. One of them is reversal, first discovered by DeBondt and Thaler (1985). Reversal effect basically means that stocks with lower long term past returns tend to have higher future returns. Although, this effect has time series predictive property, it is about the cross-sectional return spread between stocks with low past returns and stocks with high past returns. Besides this, Jegadeesh and Titman (1993) document momentum effect which means stocks with relatively higher short term past returns tend to have higher future returns for a short period of time after.

Reversal effect is explained by Fama-French three factor asset pricing model (Fama, French 1996). In other words, cross sectional return spread between reversal winner and loser stocks can be justified by their risk exposures to certain risk factors, which are size, value and market risk. However, momentum remains being an anomaly since neither CAPM nor three factor model can explain momentum spread, which is the significant average excess return difference between momentum winner and loser stocks. Researchers show the difficulty in explaining momentum (Fama, French 1996-Grundy and Martin 2001- Griffin, Ji and Martin 2003). Both effects have been existing in stock returns data even after they have been discovered (Jegadeesh and Titman 2001-Schwert 2003).

Return dynamics associated with reversal and momentum are explained by DeBondt, Thaler (1985) and Jegadeesh and Titman 2001. Basically, momentum profits only exist for up to one year, then reverse the course and turn into reversal in the long run. In this perspective, researchers tried to come up with economic stories (mostly behavioral explanations that assumes investor irrationality and existence of persistent psychological biases) to build a single framework that explains both momentum and reversal (Barberis, Schleifer, Vishny 1998-Danial, Hirshleifer, Subrahmanyam 1998). Fama (1998) suggested a rational explanation for these past returns effects, contradicting with the behavioral literature on this issue. He claimed momentum profits are due to chance events.

Lets consider one arbitrary month t. Stocks that have higher returns between month t-12 and month t-2 are likely to have higher future returns between month t and month t+12. This is the momentum effect for month t. These stocks are likely to have low returns between month t+12 and t+24 due to reversal effect for month t+12 (see Figure 1). Now lets consider momentum effect for time t+12. Stocks that have high returns due to momentum effect of time t will be among the stocks that have high short term past returns for month t+12. So these stocks should tend to have high short term future returns, which correspond to the period between month t+12 and t+24, due to the momentum effect for month t+12. In this sense, momentum and reversal dynamics look inconsistent.

We examine stock migration patterns between past return performance ranks and future return performance ranks. Performance ranks are determined with respect to cumulative returns relative to other stocks in the sample. In this way, we can sort stocks into long term past and short term past cumulative return performance ranks that will overlap with reversal and momentum portfolios. We expect that this will give us a better picture about stock return dynamics associated with momentum and reversal. Since momentum and reversal effect have been observed in portfolio averages in the previous literature, actually observing which stocks end up being winners or losers in the short term future means going deeper in understanding momentum and reversal. This is the main motivation of the paper.

We see that two subsequent momentum effects dont create a reversal effect empirically, even though it is theoretically possible. Since some past winners may end up being losers, we can have hypothetical momentum matrices that can create reversal migration if put in a consecutive order. From the first order autoregressive perspective, this is what actually should happen. Our conclusion is that it is a naive way of thinking about momentum and reversal separately, such as viewing the predictive nature of past returns as a first order autoregressive process.

We show that solution to this puzzle is considering short term and long term past return performance simultaneously to infer the likely pattern of stock migration. In other words, migration dynamics are path dependent in the sense that both long term and short term performance matter to determine the likely migration of stocks among return performance ranks.This is the main thought experiment in the paper.

Momentum migration matrix shows that short term past winners are most likely to be winners in the short term future. However, significant proportion of them actually becomes losers in the short term portfolio holding period. Same wedge shaped transition likelihood pattern is also observed for momentum losers; stocks that have the worst returns in the momentum portfolio sorting period are most likely to migrate into the worst holding period return generating group of stocks. However, these losers are second most likely to migrate into group of stocks with the highest short term holding return. This is another evidence that one way sorting depending on short or long term past stock return performance is quite crude way of distinguishing among stocks in terms of their future return performance likelihood.

This implies that momentum investing can be substantially improved by separating winners that keep winning and winners that reverse to become losers, as well as separating losers that will keep losing from losers that are about to reverse to become winners. This will definitely make momentum investing substantially improved by cleaning the reversal effect from momentum.

This separation is theoretically and empirically straightforward. Both momentum and reversal are systematic patterns in cross section of stock returns that are characterized by past return performance. Momentum formation period follows reversal formation period. For instance the time period which is between two years before until one year before sorting month is used for reversal. Momentum formation period is from one year before sorting month and a month before the sorting month for momentum. Both momentum and reversal infer about short term future return performance of stocks. All these reasons only make it very intuitive to use reversal and momentum together to get a finer sort on stocks using past return information.

Motivated by the observation that momentum is not a very efficient way of investing, we sort stocks into short term and long term past return performance quintiles. First, we get independent five momentum and five reversal portfolios and take their intersection to get twenty-five double sorted portfolios. For example, momentum winners, which are grouped in the highest momentum portfolio are partitioned into five more portfolios depending on their reversal sorting returns, namely, cumulative returns in the long term past. This gives us two extreme winner portfolios for momentum. One is stale winners which are reversal winners and momentum winners (stocks that are in the intersection of highest numbered momentum and reversal portfolios). These stocks have been top performers both for the short term and the long term. The other group is the fresh winners. These subgroup of momentum winners were worst losers in the long term past, but happened to be best winners in the short term past. In other words, they are momentum winners but reversal losers. In this sense, they are recently started their superior return performance, relatively to other momentum top winners.

Intuitively, we expect stocks that are momentum winners and reversal losers, namely fresh winners to get the highest portfolio holding period returns, since momentum and reversal effect work together, supporting each other. Similarly, we expect stocks that are momentum losers and reversal winners to have the lowest short term holding period returns.

This is indeed the case, as we confirm from building double sorted portfolios and getting average monthly excess returns of these portfolios between 1925 and 2006. "Fresh winners", which are momentum winners and reversal losers exceed "fresh losers", which are momentum losers and reversal winners, by 1.43 percent monthly average excess returns in this sample period.

This zero cost portfolio profit (profit from holding fresh winners and shorting fresh losers) is substantially bigger than both momentum and reversal zero cost portfolio profits. Momentum investing gives 0.86 percent monthly average return and reversal investing gives 0.50 percent monthly average return in the sample period between 1925 and 2006. Basically, double sorting improves on both momentum and reversal single sorting economically and statistically.

Superior average returns of double sorted portfolios indicates the importance of investigating the risk characteristics of cross sectional excess return spreads of double sorted portfolios. We want to see if there is any risk based justification of the systematic difference in returns for extreme double sorted portfolios respect to standard benchmarks.

We perform time-series CAPM, Fama-French and Carhart factor regressions on monthly portfolio returns of our 25 two-way sorted portfolios. As expected, we observe more significant abnormal returns relative to one-way sorted portfolio regressions. The alpha spread between fresh winners and fresh losers are significantly positive in all tests.

Most importantly, even though Carhart four factor model explains both reversal and momentum separately, it fails to explain fresh momentum effect. There is 0.85 percent alpha spread between fresh winners and fresh losers from Carhart model. This evidence supports that fresh momentum is significantly different from momentum and incorporating reversal fundamentally improves on momentum in terms of returns above and beyond what systematic risk captured by market, size, value and momentum, justifies.

We also observe significantly positive alpha spread between fresh and stale winners as well as significantly negative alpha spread between fresh and stale losers. All these results support our claim that two way sorting conveys significant information that one-way sorting or first order auto regressive approach cannot deliver. Significant alphas suggest that two-way sorting can be used as a highly profitable investment strategy since this combined anomaly is persistent.

We exploit firm fundamentals data and find that there is significant information content in two-way sorting, which is not present in one-way sorting of stocks (momentum or reversal). This is also confirmed by earnings data. Examining fundamentals data for double sorted portfolios can give us evidence about the origin of these abnormal profits in fresh momentum strategy. One possibility is that return spread is due to cash flows news and revisions of expected cash flows.

We follow event study methodology of Fama and French (2008). Basically, we observe average quarterly earnings shocks progression of momentum, reversal and two-way sorted portfolios from one year before to three years after the portfolio sorting month. Earnings shocks, defined as this quarters earnings minus earnings of four quarters before (scaled by stock price of four quarters before), move in a similar fashion with return spreads progression during matching time periods around sorting months.

We take earnings of one year past as the expected earnings for this year. In this perspective, earnings shocks proxy for cash flow surprises. Matching patterns between earnings shocks and returns suggest that momentum, reversal and two-way sorted portfolio profits originate as responses to these unexpected cash flow news. Stock return spreads among extreme portfolios are actually justified by the consistent cash flows news spreads for these portfolios.

To pin down the story that abnormal returns are in fact responses to cash flow news, we examine forecast revisions around portfolio sorting months. We need to make sure that investors really revise their expectations on the face of these cash flow news. Again, we find matching dynamics with portfolio returns; momentum winner portfolios that have higher returns relative to loser portfolios during the time period that spans from one year before and one year after the portfolio sorting months, also have higher analyst forecast revisions.

This spread of analyst forecast revisions is bigger for two-way sorted portfolios (between fresh winners and fresh losers). This positive spread between winners and losers turns into negative at the beginning of one year after portfolio sorting and continues being negative two more years. This exactly matches with the reversal effect return dynamics.

More interestingly, this methodology clearly shows the contemporaneously matching progression of returns, earnings surprises and earnings forecasts. Winners start beating losers shortly before sorting in terms of all three measures(profit, firm fundamentals news, revision of expectations) and keep their higher position till shortly after portfolio sorting month. Then, losers exceed winners simply due to the reversal effect until three years after portfolio sorting month.

It is quite interesting to see this gradual wave-like progression for all portfolio-spreads on all three measures. Our evidence support the view that investors continuously revise their expectations of future cash flows as response to firm fundamentals news, even though there is a predictable pattern in firm fundamentals progression. (Chen, Moise, Zhao (2009)).

In this perspective, investors are irrational because they don't figure out this predictable pattern in firm fundamentals and keep being surprised. Empirical evidence that we suggest as being explanatory for the abnormal returns of fresh momentum support the behavioral explanation of these anomalies. Simply, investors are irrational in the sense that they are unable to incorporate information present in the past stock returns. This also suggest financial market does not even hold weak form efficiency.

Finally, we check earnings announcement returns, showing that investors get surprised with earnings announcements. We show average three-day cumulative returns of momentum, reversal and double sorted portfolios around earnings announcement dates. This event study is quite useful especially because three day risk free rate (discount rate) is close to zero, so this cumulative return is due to earnings surprises.

The fact that we observe significant returns around earnings announcements imply investors revise their expectations of future cash flows unrelated to changes in discount rates. More interestingly and more relevant for the purpose of this paper, we observe announcement return spread between winners and losers, which is consistent with the return and firm fundamentals spread for momentum, reversal and double sorted portfolios. As expected, fresh momentum announcement return spread is significantly bigger relative to momentum and reversal announcement return spreads.

The rest of the paper is organized as follows. Section 2 briefly summarizes momentum and reversal effects. Section 3 explains migration methodology and its implications for our study. Section 4 and 5 examines return and risk characteristics of fresh momentum portfolios in comparison with momentum and reversal sorting. Section 6 reports firm fundamental analysis for these portfolios. Section 7 and 8 examines expected cash flow revision dynamics for double sorted portfolios. Section 9 summarizes the empirical results of an event study for post-earnings announcement returns. Finally, section 10 concludes.

2 Momentum And Reversal Effects

To prepare the set up for our empirical study, we show momentum and reversal portfolios average excess returns on Table 1. We use monthly stock return data from January 1925 to December 2006 (inclusive)from CRSP database. (We exclude stock return data from 2007 to 2008 due to a major negative macro economic shock on stock prices).

For each momentum portfolios month t, we sort stocks into short-term past return performance quintiles, depending on their cumulative returns from month t-12 to month t-2 (inclusive). We exclude one month before portfolio month t to avoid bid-ask bounce (see Fama-French 1996). Each quintile for any month t, gives one momentum portfolio for month t. First quintile contains the worst momentum performers, losers. To get the monthly momentum portfolio excess returns, we calculate value-weighted cross sectional average excess stock returns in that portfolio for each month. (We use one month lagged market capitalization of stocks to calculate portfolio weights for each month). Portfolios are re-balanced every month.

To obtain reversal portfolios, we apply the same method that we use for momentum portfolios. Only exception is that formation period for portfolio month t is between month t-24 and month t-12 since we are interested in long term past cumulative return performance of stocks. (This time, we skip one year between the end of formation period and the portfolio month, following the standard methodology).

We confirm that we have momentum effect in our sample. On table 1, we see that momentum winner portfolio (Q5) exceeds loser portfolio by 0.85 percent of average monthly excess return (time series average) in our sample period. This is significantly positive at 5 percent level with a t statistic of 4.06. We also observe that momentum is monotonic in the sense that from the worst loser portfolio to the best winner portfolio, there is monotonic increase in average monthly portfolio returns.

Similarly, reversal losers beat reversal winners by 0.50 percent of average monthly excess return with a significant t statistic of 2.83 at 5 percent level. Again, reversal pattern exists in our sample and it is monotonic like momentum. There is a monotonic decrease of short term holding period (one month) returns from worst losers to best winners. We notice that momentum spread (difference of average returns between extreme portfolio average returns) is larger than reversal spread.This suggests that momentum is somewhat a bigger anomaly that is economically more significant.

Monotonic average excess return increase form momentum losers to winners indicates momentum effect is present and monotonic decrease in average excess returns from reversal winners to losers show that reversal effect exists. These regularities also suggest predictable migration patterns from all momentum and reversal portfolios (not only extreme portfolios) to first month performance quintiles. This leads into our examination of stock migration between long term past, short term past and future short term relative return performance ranks.

3 Stock Migration

We examine stock migration patterns between past return performance ranks and future return performance ranks. We expect that this will give us a better picture about stock return dynamics associated with momentum and reversal. This is because we can distinguish further stocks in each momentum or reversal portfolio in terms of their likely destination in the short term future.

Stocks are sorted into momentum and reversal portfolios depending on their short term and long term past returns as previously done with average returns analysis. Similarly, we build first month return performance quintiles depending on one month holding return of momentum and reversal portfolios. Momentum migration matrix is an average Markovian transition matrix, which has sample frequencies of stock migrations as its entries.

For each month, we build a momentum migration matrix. This shows the empirical distribution of stock migration frequencies from momentum portfolios into one month holding return performance portfolios for that specific month. We follow the same procedure to build monthly reversal migration matrices. Average migration matrices for momentum and reversal are time series averages of these monthly migration matrices.

Table 2 summarizes momentum and reversal migration patterns. In Panel A, we have the Markovian transition matrix from momentum performance quintiles into first month return performance quintiles. For instance, stocks which are in momentum quintile 5 (MQ 5) have 28 percent probability of becoming in top first month return quintile (FQ 1). In this sense, each row contains migration probabilities of stocks for each momentum portfolio.

We see the momentum effect clearly by looking at this momentum migration matrix. Winners are likely to be winners since 28 percent is the highest number in the fifth row of the matrix. Losers are most likely to remain losers since 28 percent is again the highest number in the first row.

Reversal effect is also evident in reversal migration matrix. Stocks that have relatively the lowest long term past returns, which are reversal losers have 25 percent probability of ending up in the best performing quintile in terms of holding first month returns. This agrees with the standard reversal effect.

In the empirical finance literature, both momentum and reversal are taken to be cross sectional anomalies. These migration matrices show that they are in fact systematic time series patterns, too.

Further investigation in table 2 displays another interesting pattern for our discussion in the paper. This is the U-shaped transition probabilities distribution in each row. We see that momentum winners most likely migrate into first-month winners portfolio, confirming momentum effect and the second highest migration likelihood is 23 percent into the worst first-month losers portfolio. Similarly, momentum losers are most likely end up in the worst first month return quintile but after that the highest likelihood is for migrating to the best first-month return quintile. This means momentum winners are most likely to be winners, however they are almost as likely to become worst losers. We see a similar U-shaped migration patterns for reversal portfolios.

This indicates that migration dynamics of momentum and reversal are not uniform like average portfolio returns. This suggests it is theoretically possible to have subsequent momentum effects turn into a reversal effect. This can be possible through inter quintiles. Extreme quintiles necessarily imply the continuation of momentum or reversal depending on which effect one starts with. However, through inter quintiles, one can build theoretically feasible momentum and reversal matrices that agree with these two effects and can demonstrate the transition from momentum to reversal. At the end, this is an empirical question we address.

However, we find that this conversion between momentum and reversal does not hold. Panel C of table 2 shows the square of the momentum migration matrix and it is pretty flat. We take the square of the momentum migration matrix since reversal formation period is equal to two consecutive momentum formation periods in our methodology. In this regard, it is not the case that momentum gradually turns into reversal.

The entries in each row of the squared migration matrix are very close to each other, meaning this new migration matrix does not have significant information from the past returns about future returns . Also, squared migration matrix is clearly different than the reversal matrix, even though reversal formation period is two subsequent momentum formation periods. Most importantly, these results show that first order auto-regressive process is not enough to explain the return predictability due to these anomalies.

4 Double Sorted Portfolios

Motivated by the observation that neither momentum nor reversal is enough to predict future return performance efficiently, we sort stocks into short term and long term past return performance quintiles. What we are aiming is to use both past return horizons to incorporate the predictive pattern coming from momentum and reversal simultaneously.

First, we get five independent momentum and reversal portfolios and take their intersection to get twenty-five double sorted portfolios. These are independent sorts and partition the stock universe into 25 equal numbered stock portfolios. For example, momentum winners are separated into five more portfolios depending on their reversal sorting returns, namely, cumulative returns in the long term before sorting month (sorting period is between two years before and one year before sorting month for reversal).

Intuitively, we expect stocks that are momentum winners and reversal losers (fresh momentum winners) to get the highest holding period returns, since momentum and reversal effect work together, supporting each other. Due to momentum, these stocks should be top winners in the future short run after sorting and due to reversal, these stocks again should be future best winners since they are long term past worst losers. Similarly, we expect stocks that are momentum losers and reversal winners (fresh momentum losers) to have the lowest short term holding period returns.

Moreover, we expect that fresh winners will exceed stale winners (stocks that are both momentum and reversal winners) and fresh losers will under-perform stale losers (stocks that are both momentum and reversal losers), confirming the increased efficiency of double sorting relative to single momentum or reversal sorting. Stocks that are stale winners are likely to be winners due to momentum, however they are likely to be losers due to reversal since they were long term past winners, too. This is indeed the case, as we confirm from double sorting US stocks between 1925 and 2006.

For these stale winner or loser stocks, momentum and reversal effects work against each other. It is interesting to see which one dominate the other. Empirically, we see that momentum effect is always dominant, meaning stale winners keep winning and stale losers keep losing, though their long past performance predict the opposite.

With these thoughts and projections in mind we calculate the average monthly excess returns of double sorted portfolios on table 3. For any month t, we sort stocks into 25 portfolios depending on their long-term past return performance (t-24, t-13) and short-term past return performance (t-12, t-2) simultaneously. All the portfolios are value weighted as before. Portfolios are re-balanced each month. Portfolio holding period is one month after sorting. We could choose any number of months between one and twelve for holding period since both momentum and reversal, as well as fresh momentum hold for these different cases. The reason that we choose one month holding period is that this is the most strong case to observe these patterns.

For example, stocks that were top losers in reversal formation period and winners in momentum formation period are called fresh winners and they have on average 1.35 percent monthly excess returns. Stocks that are long term winners and short term losers are called fresh losers and they have the lowest average monthly excess return of -0.08 percent, as expected. This means there is a 1.43 percent spread on average excess returns of fresh winners and fresh losers. We expect fresh winners have the best first month return since reversal and momentum effect work in the same direction. This is confirmed with the data as shown in this table. This return spread between extreme fresh momentum quintiles is significantly larger than both momentum and reversal spreads economically and statistically. Similarly, fresh losers perform the worst among 25 portfolios.

Portfolio number 11 contains the stocks which were long term and short term losers. This portfolio has 0.25 percent average monthly return. We call them stale losers. Here reversal predicts they should be winners in the first portfolio month and momentum effect predicts the opposite. In other words, two effects work against each other. Momentum effect is dominant in the sense that stale winners do better than stale losers. We observe the average monthly return spread between stale winners and losers is 0.69 percent which is statistically and economically significant.

We see that double sorting increases the profitability of both momentum and reversal strategies by incorporating them in one strategy. One way to confirm this is that fresh momentum extreme portfolio spread is much bigger than momentum and reversal spreads as explained above. Another way is to see the difference between fresh and stale winners/losers. Fresh winners exceed stale winners by 0.43 percent monthly, which is significant at 5 percent level with a t statistic of 2.27. At the other end of the spectrum, as expected, fresh losers do worse than the stale losers by 0.33 percent monthly, again statistically significant. This is the source of higher zero cost profits of fresh momentum with respect to momentum and reversal.

This shows that our thought experiment about return dynamics in the face of considering momentum and reversal together has economic significance. We get economically and statistically larger spread between extreme fresh momentum portfolios and the improvement over stale counterparts are observed form both the winner and the loser sides of the return performance spectrum.

5 Abnormal Returns

To investigate the risk nature of cross sectional excess return spread of double sorted portfolios, we perform time-series CAPM and Fama-French factor regressions on monthly portfolio returns. First of all, we do these tests on momentum and reversal portfolios to confirm that in our sample period, these two anomalies prevail and are persistent.

First we perform time series factor regressions for momentum portfolios in order to validate that momentum is not explained by risk compensation relative to standard benchmarks. Table 4 shows that CAPM fails to explain cross sectional differences on realized returns for momentum portfolios since there is a significantly abnormal excess return difference between momentum winners and losers, which is 1.12 percent.

Fama-French three factor model also fails to explain momentum effect in this perspective since we see again significantly positive alpha from regressing momentum portfolios on size, value and market risk factor mimmicking portfolios.

Carhart four factor model explains momentum in our sample by construction since the fourth factor in this model is momentum factor itself. This validates that momentum is a unique phenomenon with a systematic pattern in stock returns that can not justified by compensation for holding risk associated with size, value and market risk.

We get expected results with reversal, too. On table 5, we see that CAPM fails to explain reversal effect. There is significantly positive alpha spread of 0.71 percent monthly controlling for market risk as modeled by CAPM. This implies that reversal investing provides an economically significant excess return beyond what the systematic risk exposure of reversal portfolios explains.

Three factor model, on the other hand captures this return predictability, giving a risk based rational explanation for reversal effect. This is mainly because of the fact that reversal portfolios behave as value stocks. Long term past losers are essentially high book to market stocks which load substantially on value premium in the three factor regression. Four-factor model also captures the reversal effect since it contains all of the three factors of the previous model.

After confirming that empirical findings of previous literature hold in our sample, we perform these regressions for our 25 two-way sorted portfolios on table 6. As expected, we observe significantly larger abnormal returns relative to one-way sorted portfolio regressions. The alpha spread between fresh winners and fresh losers are significantly positive in all tests.

CAPM regression of fresh momentum portfolios give us 1.48 percent monthly abnormal excess return spread between fresh winners and fresh losers. This spread between extreme portfolios is almost double of both momentum and reversal spreads. As expected, fresh winners have significantly larger abnormal returns relative to stale winners and fresh losers have smaller abnormal returns relative to stale losers.

Fama-French three factor model also fails to explain fresh momentum profits. We have again a high alpha spread of 1.55 percent monthly between fresh winners and fresh losers. This clearly supports that fresh momentum is bigger an anomaly than momentum itself. As with CAPM, fresh winners exceed stale winners in terms of abnormal returns again in the three factor regression.

Most importantly, even though Carhart four factor model explains both reversal and momentum separately, it fails to explain fresh momentum effect. There is 0.85 percent alpha spread between fresh winners and fresh losers. This corresponds to approximately 10.2 percent annual abnormal returns beyond what market, size, value and momentum risk justifies as compensation for holding risk. We also observe significantly positive alpha spread between fresh and stale winners as well as significantly negative alpha spread between fresh and stale losers at a higher level relative to momentum and reversal.

All these results support our claim that two way sorting conveys significant information that one-way sorting or first order auto regressive approach cannot deliver. Significant alphas suggest that two-way sorting can be used as a highly profitable investment strategy since this combined anomaly is persistent. This way, by making both momentum and reversal sorting more efficient, we can substantially increase the profitability of these investing styles.

6 Firm Fundamentals

We exploit firm fundamentals data to see if there is significant information content in two-way sorting, which is not present in one-way sorting of stocks (momentum or reversal). We follow event study methodology of Fama and French (2008). Main purpose of this section is to pin down systematic patterns in returns by relating them to fundamentals information in momentum, reversal and double sorted portfolios.

Basically, we examine quarterly earnings shocks progression of momentum, reversal and two-way sorted portfolios from one year before to three year after the portfolio sorting month and observe that they move in a similar fashion with average returns of these portfolios during matching time periods around sorting months. In our matching process between stock market data and firm fundamental data, we make sure that firm fundamental data were public information before the holding period of the relevant stock return.

All firm fundamentals data are extracted from COMPUSTAT universe covering the time period between 1985 and 2006. We define earning shocks as changes in earnings/lagged asset ratio (return on assets) between this quarter and four quarters ago. Our fundamentals data have quarterly frequency. As opposed to previous average return and risk analysis, we use terciles instead of quintiles since firm fundamentals data are noisier than stock return data. Since momentum and reversal anomalies are more distinctive with higher number of portfolios, we can only hurt our results with low number of portfolios. So our results are necessarily valid for other procedures with larger number of portfolios.

We start out investigation with momentum portfolios. In Panel A of Table 7, we table average earnings shocks around momentum portfolios. As we see momentum winners start of beating momentum losers twelve months ago in terms of earnings shocks. This relation goes until shortly after sorting month, t. This time period consistently matches with the period that momentum winners have superior returns than momentum losers. It is only natural to conclude that there is strong evidence for relating higher average returns to higher earnings shocks of winner portfolios. After two quarters post sorting, momentum losers start beating momentum winners and this is the point where we see that momentum actually starts to reverse in the sense that momentum investment strategy starts to generate negative returns.

Again, we observe intuitive and consistent earnings shocks progression for reversal. One year before sorting, reversal losers start lower than winners and gradually they exceed winners in terms of average returns. This goes as long as reversal losers have superior returns relative to winners.

When we study earnings shocks progression of double sorted portfolios in the same fashion, we see that cross-sectional differences in returns are consistent with cross-sectional differences in earnings shocks before and after portfolio sorting month. Fresh winners have monotonically increasing higher earnings shocks than fresh losers till portfolio sorting month, t.

This superior performance in earnings shocks monotonously decreases and eventually turns into reversal as fresh losers get higher earnings shocks than fresh winners, beginning one year after portfolio sorting month, t.

It is common practice in empirical finance literature to take twelve months lagged earnings as expected earnings for this month. In this sense, earnings shocks are unexpected earnings component of realized earnings. They represent earnings surprises.

The fact that fresh momentum winners have positive earnings shocks after portfolio sorting month supports the market irrationality view. By taking twelve month lagged earnings as expected earnings, we are concluding that investors dont perceive any of the predictable trend and reversion patterns in earnings.

Same pattern exists between fresh and stale winners. Fresh winners do better than stale winners one year before and one year after month t in terms of returns and earnings shocks. However, reversal comes much later for fresh and stale winners, namely three years later, which is expected since, both portfolios are short term winners. This pattern is also consistent for fresh loser-stale loser earnings shocks spread. From earnings shocks patterns, we conclude that fresh and stale winners/losers are fundamentally different.

7 Analyst Earnings Forecast Revisions

We know that stock prices are forward looking and earning shocks affect stock prices if they make investors revise their forecasts on future cash flows. With this motivation, we investigate analysts one-year forward earnings forecast revisions for momentum, reversal and double sorted portfolios. We expect continuous forecasts revisions progression around portfolio sorting months which is consistent with return and earnings shocks dynamics discussed above, to be able to support market irrationality explanation mentioned previously.

Our analyst forecasts data is from I/B/E/S data set. We define forecast revisions as this months forecast minus the forecast of twelve months ago, scaled by the stock price of twelve months ago. We use quarterly data.

Table 8 shows quarterly changes in 4 quarter forward earnings forecasts revisions.This table confirms that investors really get surprised around portfolio sorting month since forecast revisions follow the same progression pattern as earnings shocks and returns of momentum, reversal and double sorted portfolios.

In Panel A, we see that momentum winners start having lower revisions in twelve month before portfolio sorting month, t relative to momentum winners. This difference gradually increases and becomes positive right before portfolio sorting month and keep being positive after this point on till one year later. Finally, winners-losers spread become negative. This is the same pattern with return and earnings shocks progression of momentum portfolios, having momentum and reversal dynamics around portfolio sorting month.

Panel B gives us similar results. Reversal winners beat reversal losers from shortly before portfolio month until 24 months after. This is the time period which higher returns are obtained by reversal winners. We observe that this period overlaps with the shifted momentum period to the right. This confirms reversal effect follows after momentum effect when we consider post portfolio sorting returns.

Panel C summarizes these forecast revisions for double sorted portfolios. As expected, we observe a similar but more dramatic pattern for fresh winner- fresh loser spread than the one with momentum. Fresh winners exceed fresh losers from three quarters before the portfolio sorting month t and this goes on until two years after. This clearly shows double sorting effect in terms of higher returns compared to both momentum and reversal is confirmed with analyst forecast revisions for future earnings. However, time period that fresh winners beat fresh losers in terms of forecast revisions is slightly shifted to the right. This is possibly due to reversal component in the double sorting.

We see that progression of forecast revisions for fresh winner minus stale winner portfolios has the exact same pattern with reversal winner minus loser portfolio. Since we control for momentum and check the reversal effect, it is natural we got this result. This confirms that after controlling for momentum, we still have the reversal effect. For fresh losers minus stale loser portfolio we can make the same argument. Again, we observe reversal effect even after we control for momentum.

8 Long Term Earnings Forecasts

We have further evidence that market does not understand the predictable pattern in earnings shocks and keep revising their forecasts. This shows irrationality of market participants since they misprice earnings news and revise their expectations to correct this mispricing continuously. Otherwise, we would observe persistent revisions in long term earnings growth forecasts.

Table 9 summarizes long term earnings growth forecast revisions dynamics around portfolio sorting month. Long term earnings growth rate forecast revisions are quarterly differences between subsequent forecasts. Since there is no seasonality, we choose to analyze quarterly changes rather than 12 month changes.

We observe similar patterns with earnings shocks progressions. This means forecast revisions are not persistent and follow earnings surprises quarter by quarter.

Panel A of table 9 summarizes long term growth revisions for momentum portfolios. Momentum winners start having lower revisions in twelve month before portfolios sorting month, t relative to momentum losers. This difference gradually increases and becomes positive right before portfolio sorting month and keep being positive after this point on till one year later. Finally, winners-losers spread become negative. This is the same pattern with return and earnings shocks progression of momentum portfolios.

We see that convergence pattern from momentum into reversal is shifted to the right, compared to the one-year forward earnings forecasts revisions progression. This suggests investors are relatively more sluggish to revise their long term expectations.

Panel B summarizes long term growth revisions for reversal portfolios which are consistent with quarter by quarter changing of expectations story. We include this panel since it is useful when we examine the forecast revision patterns of two-way sorted portfolios.

We get consistent results with double sorted portfolios as shown in Panel C. Fresh winners exceed fresh losers starting from two quarters before portfolio sorting month until three years after since reversal and momentum effects work together to create this spread.

Controlling for momentum, we see that reversal still plays a significant part because fresh winners have higher forecast revisions than stale winners before and after portfolio sorting month.

Similar argument holds in the case of fresh and stale losers forecast revision spread. Again these progressions are consistent with return and earnings shocks dynamics of double sorted portfolios.

9 Earnings Announcement Returns

Finally, we check earnings announcement returns, showing that investors get surprised with earnings announcements. We examine average three-day cumulative returns of momentum, reversal and double sorted portfolios around earnings announcement dates. This event study is quite useful especially because three day risk free rate (discount rate) is close to zero, so this cumulative return is due cash flow news part of earnings surprises.

Panel A of table 10 shows average announcement returns for momentum portfolios. The average announcement returns are significantly positive for all momentum portfolios. As expected there is a significant 0.41 percent return spread between momentum winners and losers.

As we can see on Panel B, we find significantly positive average announcement returns for reversal portfolios and reversal losers exceed reversal winners by 0.44 percent which is significantly positive at 5 percent level. This supports the earnings surprises explanation of momentum and reversal cross-sectional return differences.

We obtain consistent results for double sorted portfolios in Panel C. All double sorted portfolios have significant average announcement returns. Fresh winners exceed fresh losers by 0.86 percent which is more than both momentum and reversal winner-loser spreads. This number is significant with a t statistic of 6.17. So double sorting improves on momentum and reversal sorting also in terms of earnings announcement return spread between winners and losers. Fresh winners have 0.22 percent more average announcement returns than stale winners do and fresh losers have 0.73 percent less announcement returns than stale losers do.

All these numbers are significantly positive in statistical and economic sense. All of these results support our argument that return spreads between winners and losers, as well as fresh winners/losers and stale winners/losers are due to price adjustments as response to earnings surprises.

The fact that we observe significant returns around earnings announcements imply investors revise their expectations of future cash flows unrelated to changes in discount rates. More interestingly, we observe significant average announcement return spreads between winners and losers for all anomalies, which are consistent with the return and firm fundamentals spreads for momentum, reversal and double sorted portfolios.

As expected, fresh momentum average announcement return spread is significantly bigger relative to momentum and reversal average announcement return spreads.

10 Conclusion

With the motivation of solving the mentioned inconsistency of momentum and reversal effect in terms of explaining stock return dynamics, we examined migration patterns of stocks among momentum, reversal and first month return performance ranks.

This thought experiment helped us understand better how these two phenomena exist together. Two-way sorting respect to long term (reversal) and short term (momentum) past returns is found to bring key information to explain stock return dynamics.

Momentum sorting is shown to be inefficient in terms of predicting stock migrations from short term past return performance into short term future return performance.

Mainly, we have a higher average monthly return spread between fresh winners and fresh losers, compared to the spreads between winners and losers in both momentum and reversal portfolios.

Double sorting also creates important economic value from an investment perspective since two-way sorting creates higher positive alphas from standard factor pricing models, including Carhart four factor model.

Significant information content of two-way sorting is confirmed with firm fundamentals. Fresh winner and fresh loser portfolios have different earnings shocks progressions between one year before and three years after portfolio sorting months. This difference reflects upon investor expectations as observed from earnings forecast revision and post-earnings announcement return patterns for fresh momentum portfolios.

Matching contemporaneous patterns of return, earnings shocks and expected earnings revisions for fresh momentum portfolios, justify the return spreads among these portfolios being fundamental.

These ”fresh” systematic patterns in average returns are due to investor irrationality coming from the fact that investors dont understand the predictable pattern in earnings progression and keep revising their expectations on future cash flows, which turn into contemporaneous returns.

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Table 1 : Average Excess Returns

This table reports time-series average of first-month excess returns of momentum and reversal portfolios. Price momentum portfolios are formed based on cumulative monthly returns from month t-12 to t-2. Price reversal portfolios are formed based on cumulative monthly returns from month t-24 to t-13. Portfolios are rebalanced at the begining of each month. The sample period is from 1925 to 2006. Portfolios are designated with momentum (reversal) formation period rank quintile. Excess returns are percentages.

Panel A: Price Momentum							
P1	P2	P3	P4	P5	P5-P1	(S.E.)	(t)
0.20	0.47	0.58	0.76	1.05	0.85	(0.21)	(4.06)
Panel B: Price Reversal							
R1	R2	R3	R4	R5	R1-R5	(S.E.)	(t)
1.06	0.83	0.74	0.71	0.56	0.50	(0.18)	(2.83)

Table 2 : Migration

This table reports average migration patterns of stocks from momentum (reversal) quintiles, MQ (RQ), into first month return quintiles, FQ. Price momentum portfolios are formed based on cumulative monthly returns from month t-12 to t-2. Price reversal portfolios are formed based on cumulative monthly returns from month t-24 to t-13. Portfolios are rebalanced at the begining of each month. The sample period is from 1925 to 2006. Portfolios are designated with momentum (reversal) formation period rank quintile. Following tables are transition probability matrices from momentum (reversal) quintiles into first month return performance quintiles.

Panel A: Momentum Migration

	FQ				
MQ	1	2	3	4	5
1	0.28	0.19	0.16	0.15	0.23
2	0.14	0.22	0.25	0.23	0.15
3	0.11	0.22	0.26	0.26	0.14
4	0.13	0.21	0.22	0.26	0.18
5	0.23	0.18	0.13	0.19	0.28

Panel B: Reversal Migration

	FQ				
MQ	1	2	3	4	5
1	0.24	0.18	0.16	0.17	0.25
2	0.13	0.21	0.25	0.24	0.16
3	0.11	0.22	0.26	0.26	0.15
4	0.14	0.22	0.21	0.26	0.17
5	0.23	0.20	0.14	0.19	0.24

Panel B: Momentum Migration Squared

	FQ				
MQ	1	2	3	4	5
1	0.20	0.20	0.20	0.21	0.21
2	0.16	0.21	0.21	0.22	0.18
3	0.16	0.21	0.22	0.23	0.18
4	0.17	0.21	0.21	0.23	0.19
5	0.19	0.20	0.19	0.21	0.21

Table 3 : Fresh Momentum Returns

This table reports average first-month excess returns of fresh momentum portfolios. Price momentum portfolios are formed based on cumulative monthly returns from month t-12 to t-2. Price reversal portfolios are formed based on cumulative monthly returns from month t-24 to t-13. Portfolios are re-balanced at the beginning of each month. The sample period is from 1925 to 2006. Portfolios are designated with momentum and reversal formation period rank quintile. Portfolios are value-weighted. Returns are in percentages.

	MQ				
RQ	1	2	3	4	5
1	0.25	0.57	0.89	0.93	1.35
2	0.14	0.53	0.69	0.83	1.27
3	0.04	0.47	0.60	0.83	1.26
4	-0.07	0.32	0.40	0.74	1.01
5	-0.08	0.17	0.38	0.66	0.91
15-51	1.43				
S.E	0.22				
t	6.48				
15-55	0.43				
S.E	0.19				
t	2.27				
51-11	-0.33				
S.E	0.12				
t	-2.74				

Table 4 : Abnormal Returns-Momentum

This table shows alphas from regressions of momentum portfolios excess returns on market factor, Fama-French HML , SMB and momentum factors. Momentum portfolios are formed based on cumulative monthly returns from month t-12 to t-2. Portfolios are designated with momentum formation period rank quintile. Portfolios are re-balanced at the beginning of each month. The sample period is from 1925 to 2006. All portfolios are value-weighted. ** indicates statistical significance at the 5 percent level. Alphas are in percentages.

Panel A: CAPM-ALPHA

M1	M2	M3	M4	M5	M5-M1
-0.67**	-0.21	-0.04	0.18	0.45**	1.12**

Panel B: Fama-French 3 Factor-ALPHA

M1	M2	M3	M4	M5	M5-M1
-0.83**	-0.31**	-0.10	0.18	0.49**	1.32**

Panel C: Carhart 4 Factor-ALPHA

M1	M2	M3	M4	M5	M5-M1
0.00	0.14	0.06	0.03	0.00	0.00

Table 5 : Abnormal Returns-Reversal

This table shows alphas from regressions of reversal portfolios excess returns on market factor, Fama-French HML , SMB and momentum factors.Price reversal portfolios are formed based on cumulative monthly returns from month t-24 to t-13. Portfolios are designated with reversal formation period rank quintile. Portfolios are re-balanced at the beginning of each month. The sample period is from 1925 to 2006. All portfolios are value-weighted. ** indicates statistical significance at the 5 percent level. Alphas are in percentages.

Panel A: CAPM-ALPHA

R1	R2	R3	R4	R5	R1-R5
0.70**	0.35**	0.30**	0.24	-0.01	0.71**

Panel B: Fama-French 3 Factor-ALPHA

R1	R2	R3	R4	R5	R1-R5
0.18	0.02	0.07	0.06	-0.07	0.24

Panel C: Carhart 4 Factor-ALPHA

R1	R2	R3	R4	R5	R1-R5
-0.03	-0.02	0.00	0.04	-0.03	0.00

Table 6 : Abnormal Returns-Fresh Momentum

This table shows alphas from regressions of two-way sorted portfolio excess returns on market factor, Fama-French HML , SMB and momentum factors. Portfolios are designated with momentum and reversal formation period rank quintile. Price momentum portfolios are formed based on cumulative monthly returns from month t-12 to t-2. Price reversal portfolios are formed based on cumulative monthly returns from month t-24 to t-13. Portfolios are rebalanced at the beginning of each month. The sample period is from 1925 to 2006. All portfolios are value-weighted. ** indicates statistical significance at the 5 percent level. Alphas are in percentages.

Panel A: CAPM-Alpha

	MQ				
RQ	1	2	3	4	5
1	0.13	0.47	0.78	0.84	1.26
2	0.03	0.46	0.62	0.77	1.19
3	-0.08	0.37	0.53	0.76	1.20
4	-0.15	0.26	0.34	0.68	0.96
5	-0.23	0.11	0.31	0.58	0.84
Q15-Q51	1.48**				
Q15-Q55	0.41**				
Q51-Q11	-0.35**				

Panel B: Fama-French 3 Factor-Alpha

	MQ				
RQ	1	2	3	4	5
1	0.04	0.35	0.67	0.76	1.17
2	-0.05	0.38	0.56	0.68	1.11
3	-0.17	0.26	0.49	0.69	1.13
4	-0.27	0.21	0.28	0.61	0.94
5	-0.38	0.05	0.26	0.52	0.79
Q15-Q51	1.55**				
Q15-Q55	0.38**				
Q51-Q11	-0.42**				

Panel C: Carhart 4 Factor-Alpha

	MQ				
RQ	1	2	3	4	5
1	1.16	1.18	1.33	1.14	1.31
2	0.90	1.06	1.05	0.95	1.09
3	0.80	0.93	0.89	0.90	1.10
4	0.64	0.75	0.61	0.76	0.87
5	0.45	0.45	0.59	0.68	0.77
Q15-Q51	0.85**				
Q15-Q55	0.54**				
Q51-Q11	-0.70**				

Table 7 : Changes in ROA

This table reports 12-month changes in return on assets in percentage for the price momentum, price reversal and price fresh momentum portfolios. ROA is measured as the ratio of income before extraordinary items to lagged total assets . Price momentum portfolios are formed based on cumulative monthly returns from month t-12 to t-2. Price reversal portfolios are formed based on cumulative monthly returns from month t-24 to t-13. Portfolios are re-balanced at the beginning of each month. The sample period is from 1985 to 2006. Portfolios are designated with momentum and reversal formation period rank terciles. ** indicates statistical significance at the 5 percent level.

Panel A: Momentum

					Month						
MQ	t-12	t-9	t-6	t-3	t	t+3	t+6	t+9	t+12	t+24	t+36
1	-0.55	-0.84	-1.08	-1.12	-0.92	-0.26	-0.02	0.17	0.26	0.27	0.18
2	-0.05	-0.05	-0.06	-0.09	-0.14	-0.55	-0.20	-0.03	0.02	-0.01	-0.12
3	0.34	0.56	0.69	0.64	0.36	-0.20	-0.19	-0.17	-0.14	-0.08	-0.09
Q3-Q1	0.89**	1.39**	1.78**	1.75**	1.28**	0.06	-0.21**	-0.34**	-0.40**	-0.35**	-0.28**

Panel B: Reversal

					Month						
RQ	t-12	t-9	t-6	t-3	t	t+3	t+6	t+9	t+12	t+24	t+36
1	-0.28	-0.10	0.11	0.13	0.05	0.05	0.04	0.01	-0.02	-0.12	-0.17
2	0.00	0.01	-0.07	-0.10	-0.11	-0.12	-0.13	-0.15	-0.16	-0.02	-0.07
3	0.19	-0.03	-0.24	-0.38	-0.43	-0.43	-0.43	-0.37	-0.35	-0.21	-0.05
Q1-Q5	-0.47**	-0.07	0.36**	0.50**	0.48**	0.48**	0.47**	0.38**	0.33**	0.09	-0.12**

Panel C: Fresh Momentum

						Month						
	MQ	t-12	t-9	t-6	t-3	t	t+3	t+6	t+9	t+12	t+24	t+36
RQ	1	-0.77	-0.88	-0.92	-0.94	-0.65	-0.15	0.19	0.27	0.25	-0.03	-0.13
1	2	-0.21	-0.09	0.01	0.05	-0.02	-0.11	-0.04	0.00	0.03	-0.11	-0.05
	3	0.07	0.55	1.08	1.11	0.74	0.36	0.00	-0.17	-0.29	-0.23	-0.28
	1	-0.40	-0.64	-0.87	-0.77	-0.57	-0.38	-0.17	-0.08	-0.14	0.09	0.01
2	2	-0.03	-0.03	0.01	-0.04	-0.09	-0.07	-0.11	-0.13	-0.08	0.03	-0.03
	3	0.39	0.63	0.53	0.44	0.27	0.05	-0.10	-0.23	-0.27	-0.17	-0.20
	1	-0.30	-0.76	-1.19	-1.34	-1.22	-0.88	-0.47	-0.22	-0.19	0.01	0.05
3	2	0.15	0.01	-0.10	-0.23	-0.28	-0.33	-0.42	-0.30	-0.28	-0.10	-0.11
	3	0.71	0.66	0.57	0.45	0.23	-0.05	-0.37	-0.56	-0.56	-0.51	-0.08
	13-31	0.37**	1.31**	2.26**	2.45**	1.96**	1.24**	0.47**	0.05	-0.10**	-0.24**	-0.33**
	13-33	-0.64**	-0.11**	0.51**	0.66**	0.51**	0.42**	0.37**	0.39**	0.27**	0.28**	-0.20**
	31-11	0.47**	0.12**	-0.27**	-0.40**	-0.57**	-0.73**	-0.65**	-0.49**	-0.44**	0.03	0.18**

Table 8 : Analyst Forecast Revisions

This table reports 12-month changes in 4 quarter-ahead Earnings Forecasts, in percentage (scaled by stock price of 12 months ago) from 3 quarters ago to the beginning of next quarter for the price momentum , price reversal and price fresh momentum portfolios. Price momentum portfolios are formed based on cumulative monthly returns from month t-12 to t-2. Price reversal portfolios are formed based on cumulative monthly returns from month t-24 to t-13. Portfolios are re-balanced at the beginning of each month. The sample period is from 1985 to 2006. Portfolios are designated with momentum and reversal formation period rank terciles. ** indicates statistical significance at the 5 percent level.

Panel A: Momentum

					Month						
MQ	t-12	t-9	t-6	t-3	t	t+3	t+6	t+9	t+12	t+24	t+36
1	0.10	-0.06	-0.24	-0.30	-0.09	0.10	0.31	0.38	0.25	0.20	
2	0.14	0.14	0.12	0.12	0.10	0.14	0.11	0.11	0.08	0.14	0.12
3	0.27	0.35	0.58	0.61	0.59	0.56	0.30	0.14	0.09	0.09	0.14
Q3-Q1	0.18**	0.41**	0.78**	0.91**	0.83**	0.54**	0.19**	-0.18**	-0.30**	-0.17**	-0.06

Panel B: Reversal

					Month						
RQ	t-12	t-9	t-6	t-3	t	t+3	t+6	t+9	t+12	t+24	t+36
1	-0.06	0.01	0.16	0.26	0.31	0.32	0.31	0.27	0.23	0.18	0.14
2	0.14	0.15	0.11	0.12	0.13	0.12	0.13	0.12	0.13	0.14	0.13
3	0.35	0.24	0.13	0.07	0.05	0.06	0.06	0.09	0.10	0.15	0.16
Q1-Q5	-0.41**	-0.23**	0.03	0.18**	0.27**	0.27**	0.25**	0.18**	0.14**	0.03	-0.02

Panel C: Fresh Momentum

					Month							
	MQ	t-12	t-9	t-6	t-3	t	t+3	t+6	t+9	t+12	t+24	t+36
RQ	1	-0.16	-0.22	-0.31	-0.27	-0.17	0.02	0.21	0.36	0.41	0.25	0.21
1	2	-0.09	0.00	0.06	0.11	0.14	0.16	0.22	0.23	0.20	0.19	0.10
	3	0.04	0.20	0.62	0.80	0.80	0.67	0.44	0.24	0.17	0.14	0.14
	1	0.04	-0.03	-0.17	-0.18	-0.14	-0.05	0.01	0.20	0.27	0.22	0.13
2	2	0.12	0.12	0.08	0.11	0.10	0.10	0.10	0.10	0.09	0.13	0.12
	3	0.25	0.33	0.38	0.40	0.39	0.27	0.19	0.10	0.09	0.08	0.12
	1	0.31	0.04	-0.23	-0.34	-0.31	-0.15	-0.02	0.14	0.22	0.24	0.23
3	2	0.30	0.21	0.15	0.11	0.07	0.05	0.05	0.06	0.07	0.14	0.13
	3	0.43	0.43	0.42	0.39	0.32	0.22	0.14	0.08	0.03	0.10	0.14
	13-31	-0.27**	0.15**	0.85**	1.14**	1.12**	0.82**	0.46**	0.11**	-0.05	-0.11**	-0.09
	13-33	-0.39**	-0.24**	0.20**	0.40**	0.48**	0.45**	0.31**	0.16**	0.14**	0.04	0.00
	31-11	0.47**	0.26**	0.08	-0.07	-0.15**	-0.17**	-0.23**	-0.23**	-0.19**	0.00	0.02

Table 9 : Analyst Forecast Revisions-Long Term Growth

This table reports quarterly changes in long term EPS growth forecasts in percentage for the price momentum , price reversal and price fresh momentum portfolios. Price momentum portfolios are formed based on cumulative monthly returns from month t-12 to t-2. Price reversal portfolios are formed based on cumulative monthly returns from month t-24 to t-13. Portfolios are re-balanced at the beginning of each month. The sample period is from 1985 to 2006. Portfolios are designated with momentum and reversal formation period rank terciles. ** indicates statistical significance at the 5 percent level.

Panel A: Momentum

					Month						
MQ	t-12	t-9	t-6	t-3	t	t+3	t+6	t+9	t+12	t+24	t+36
1	-0.30	-0.48	-0.68	-0.84	-0.93	-0.78	-0.64	-0.50	-0.38	-0.20	-0.19
2	-0.15	-0.17	-0.17	-0.15	-0.15	-0.16	-0.16	-0.16	-0.14	-0.11	-0.08
3	-0.34	-0.24	-0.12	-0.06	-0.30	-0.13	-0.23	-0.28	-0.28	-0.27	-0.20
Q3-Q1	-0.04	0.25**	0.56**	0.78**	0.91**	0.66**	0.41**	0.22**	0.10**	-0.08	0.00

Panel B: Reversal

					Month						
RQ	t-12	t-9	t-6	t-3	t	t+3	t+6	t+9	t+12	t+24	t+36
1	-0.48	-0.43	-0.35	-0.30	-0.27	-0.22	-0.22	-0.22	-0.18	-0.16	-0.13
2	-0.13	-0.12	-0.11	-0.12	-0.12	-0.12	-0.12	-0.10	-0.11	-0.06	-0.08
3	-0.09	-0.16	-0.25	-0.30	-0.34	-0.35	-0.32	-0.29	0.25	-0.23	-0.15
Q1-Q3	-0.39**	-0.27**	-0.09	0.00	0.07	0.13**	0.10**	0.07	-0.43**	0.07	0.02

Panel C: Fresh Momentum

					Month							
	MQ	t-12	t-9	t-6	t-3	t	t+3	t+6	t+9	t+12	t+24	t+36
RQ	1	-0.45	-0.54	-0.59	-0.65	-0.67	-0.48	-0.41	-0.34	-0.24	-0.09	-0.17
1	2	-0.31	-0.27	-0.22	-0.18	-0.17	-0.12	-0.11	-0.13	-0.09	-0.12	-0.07
	3	-0.67	-0.50	-0.25	-0.09	0.02	-0.03	-0.11	-0.16	-0.19	-0.25	-0.14
	1	-0.17	-0.24	-0.32	-0.40	-0.38	-0.34	-0.24	-0.17	-0.16	-0.03	-0.07
2	2	-0.07	-0.07	-0.07	-0.04	-0.06	-0.06	-0.07	-0.07	-0.07	-0.03	-0.05
	3	-0.19	-0.07	0.02	0.03	0.02	-0.04	-0.10	-0.07	-0.14	-0.12	-0.14
	1	-0.12	-0.34	-0.62	-0.80	-0.88	-0.70	-0.50	-0.39	-0.32	-0.29	-0.22
3	2	-0.03	-0.11	-0.14	-0.17	-0.16	-0.20	-0.20	-0.19	-0.15	-0.14	-0.05
	3	-0.12	-0.05	-0.02	0.00	-0.05	-0.17	-0.27	-0.31	-0.29	-0.25	-0.20
	13-31	-0.55**	-0.16**	0.37**	0.71**	0.91**	0.69**	0.39**	0.23**	0.13**	0.05	0.07
	13-33	-0.55**	-0.45**	-0.23**	-0.10**	0.08	0.14**	0.15**	0.15**	0.10**	0.00	0.05
	31-11	0.33**	0.20**	-0.03	-0.15**	-0.22**	-0.24**	-0.10**	-0.05	-0.08	-0.20**	-0.05

Table 10 : Earnings Announcement Returns

This table shows 3 -day average cumulative returns of momentum, reversal and fresh momentum portfolios around yearly EPS (earnings per share) announcements . Window period is from one day before announcement to one day after. Price momentum portfolios are formed based on cumulative monthly returns from month t-12 to t-2. Price reversal portfolios are formed based on cumulative monthly returns from month t-24 to t-13. All portfolios are equally weighted. Portfolios are re-balanced at the beginning of each month. Sample period is from 1985 to 2005. Portfolios are designated with momentum and reversal formation period rank terciles. Returns are in percentages.

Panel A: Momentum

MQ	Mean	S.E.	t
1	0.29	0.09	3.17
2	0.55	0.06	8.93
3	0.70	0.07	9.61
Q3-Q1	0.41	0.09	4.78

Panel B: Reversal

MQ	Mean	S.E.	t
1	0.77	0.08	9.18
2	0.51	0.06	7.84
3	0.33	0.08	4.04
Q1-Q3	0.44	0.08	5.35

Panel B: Fresh Momentum

Mean	MQ		
RQ	1	2	3
1	0.67	0.74	0.80
2	0.34	0.41	0.75
3	-0.06	0.40	0.59

S.E.	MQ		
RQ	1	2	3
1	0.17	0.12	0.14
2	0.15	0.08	0.12
3	0.16	0.13	0.13

t	MQ		
RQ	1	2	3
1	3.86	6.05	5.81
2	2.20	5.12	6.40
3	-0.35	3.21	4.39

profit	Mean	S.E.	t
13-31	0.86	0.14	6.17
13-33	0.22	0.12	1.73
31-11	-0.73	0.15	-4.78

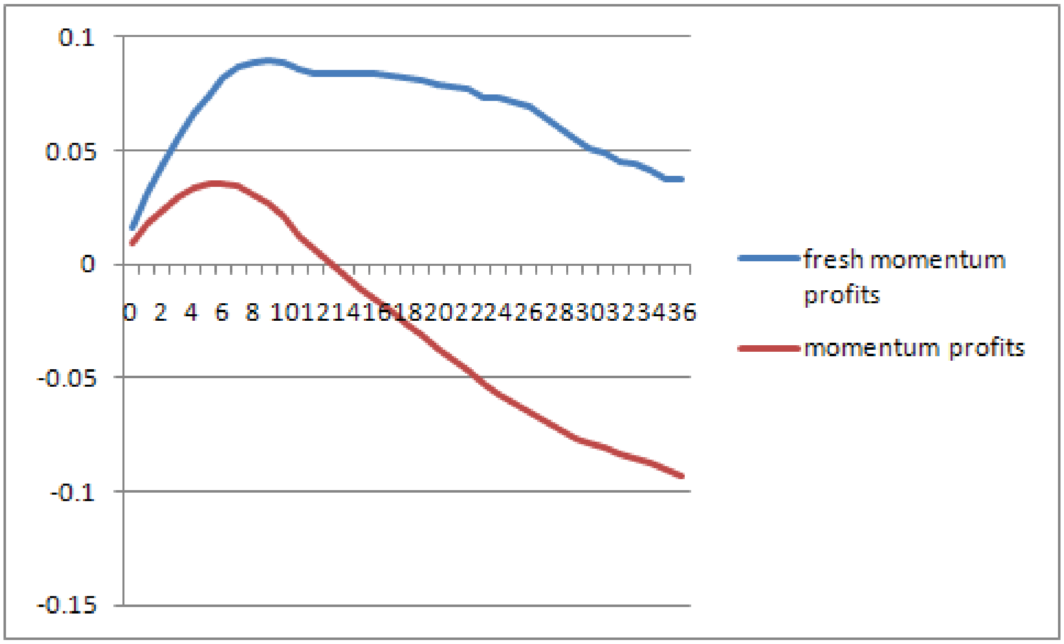

Figure 1 Cumulative Profit

This figure shows cumulative monthly profits from holding winner portfolio and shorting loser portfolio for momentum and fresh momentum strategies. Initial time period is the portfolio sorting month.