Can Information Explain the Return Predictive Power of Institutional Ownership?

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ABSTRACT

Percentage change in the number of institutional investors (N_Chg) has strong and robust predictive power of short-run future stock returns. After the negative autocorrelation in change in the fraction of shares owned by institutions (Pct_Chg) is controlled, Pct_Chg also strongly positively predicts short-run future stock returns. Moreover, contrary to conventional wisdom, the short-run return predictive power of N_Chg and Pct_Chg is not driven by superior information of institutional investors. In fact, institutional investors (on average) have no informational advantage over individual investors regarding future corporate operating performance innovations. Finally, the short-run return predictive power of N_Chg and Pct_Chg is found to be stronger for the stocks more prone to speculative trading, which is consistent with an alternative 'noise trading' explanation to the documented anomaly.

Current literature offer different results on the cross-sectional relationship between changes in institutional ownership and future stock returns. Gompers and Metrick (2001) find no significant relation between changes in institutional ownership (i.e., the fraction of shares owned by institutions) and next quarter's returns, although they find a positive relation between institutional holdings and next quarter's returns. In contrast, Nofsinger and Sias (1999) find that changes in institutional ownership positively forecast next year's returns; while Cai and Zheng (2004) document a negative relation between changes in institutional ownership and next quarter's returns. Yan and Zhang (2009), however, find evidence of a positive relation only between changes in short-term institutional ownership and future (both next quarter's and next year's) returns. Sias, Starks and Titman (2006) find that changes in the number of institutional shareholders are positively correlated with next quarter's returns, while changes in institutional ownership have an insignificant correlation with next quarter's returns.

Nofsinger and Sias (1999), Yan and Zhang (2009), and Sias, Starks and Titman (2006) all attribute the positive relations they document into the informational advantage of institutional investors. That is, institutional investors are on average better informed, thus their trading forecasts future stock returns. In contrast, Gompers and Metrick (2001) and Cai and Zheng (2004) attribute their results into the price pressure caused by institutional demand. [1] In addition to these explanations, the link between changes in institutional ownership and future stock returns may arise simply because changes in institutional ownership serve as a proxy for changes in the strength of corporate governance. [2] [3] Alternatively, the relation could be

[1] Gompers and Metrick (2001) argue that persistent institutional demand shocks result in a positive relation between institutional holdings and future returns; while Cai and Zheng (2004) believe that the increase in stock prices caused by institutional demand results in a negative relation between changes in institutional ownership and future returns.

[2] Institutional shareholders are usually large shareholders. Classical corporate finance theories suggest that large shareholders have the incentive to monitor the manager of the firm, thus avoid the free-rider problem of monitoring encountered by atomistic shareholders (e.g., Jensen and Meckling (1976), and Shleifer and Vishney (1986)). This view has been corroborated by empirical evidences (e.g., Bertrand and Mullainathan (2001), and Hartzell and Starks (2003)).

[3] It has been documented that the strength of corporate governance positively affects future stock returns. See, e.g., Gompers, Ishii and Metrick (2003) and Cremers and Nair (2005).

driven by the fact that institutional investors base their trades on past return/firm characteristics known to be related to future returns. [4] Finally, it is also possible that the link arises from the association of changes in institutional ownership with some unknown risk factor.

In this paper, I study the return predictive power of two institutional ownership variables – change in the fraction of shares of a stock owned by institutions (i.e., Pct_Chg), which is widely studied in extant literature, and percentage change in the number of institutions holding the stock (i.e., N_Chg). The paper presents several interesting findings.

First, corroborating the finding of Sias, Starks and Titman (2006), I find that N_Chg strongly predicts short-run future (especially next quarter's) stock returns. A long-short strategy that buys the largest N_Chg decile and shorts the smallest decile and rebalance every quarter would generate a Carhart (1997) 4-factor alpha of 2.04% per quarter (8.41% per annum) between 1982 and 2006. Furthermore, this return predictive power of N_Chg is very robust – it is independent of size, value, and momentum (as well as other return/firm characteristics known to be related to future stock returns); it exists in both the full sample period and subperiods; it exists even when a two-month waiting period is added (each quarter) before portfolio formation, thus is fully tradable.

Second, I find that Pct_Chg appears to have no predictive power on future stock returns; however, after the negative autocorrelation in Pct_Chg is controlled, Pct_Chg also strongly positively predicts short-run future (next quarter's) stock returns. Therefore, Pct_Chg in fact has return predictive power, and the insignificant relation documented in prior studies is caused by both the negative autocorrelation in Pct_Chg and the strong positive relation between Pct_Chg and contemporaneous returns. [5] I also find that the positive return

[4] For example, recent studies show that institutional investors are momentum traders (e.g., Cai and Zheng (2004), and Sias (2004, 2007)).

[5] This result is in contrast with the findings of Gompers and Metrick (2001), Sias, Starks and Titman (2006) and Yan and Zhang (2009), as these papers do not control for the negative autocorrelation in Pct_Chg.

predictive power of N_Chg and Pct_Chg is short-run in nature – the relations start to reverse after two quarters.

Third, I find that the short-run strong return predictive power of N_Chg and Pct_Chg is *not* driven by the informational advantage of institutional investors, as controlling for earnings news and idiosyncratic volatility do not eliminate or even reduce the predictive power. Surprisingly, new evidence from the paper clearly indicates that institutional investors on aggregate have no informational advantage over individual investors – stocks purchased by institutions demonstrate increasingly better operating performance innovations (in terms of seasonal earnings growth, seasonal net operating cash flow growth, and seasonal sales growth) than stocks sold by institutions only before institutional trading (purchase/sale) is made; once institutional trading has been made, the difference in operating performance innovations abruptly reverses direction and demonstrates a steep downward-sloping trend and even quickly becomes negative (in the fourth quarter after institutional trading). If institutions really did (on average) possess superior information over individual investors, one would expect an increasingly upward-sloping trend in operating performance innovations difference between stocks purchased by institutions and those sold by institutions after institutional trading has been made (before the reversal finally occurs), and would never expect a reversal at around the timing of institutional trading.

Furthermore, I find that stocks purchased by institutions have significantly higher current valuations (in terms of Tobin's Q), which does not support the hypothesis that the documented return predictive power of N_Chg and Pct_Chg is driven by institutions possessing superior information in picking undervalued stocks. Other potential explanations (mentioned earlier) are also found to lack power in accounting for the findings of this paper.

Finally, I offer an alternative potential explanation to the documented institutional ownership anomaly: the anomaly might be driven by speculative trading of noise traders.

Noise traders view institutional trading as conveying valuable information, thus they follow suit and trade on 'noise' (Black (1986)). The speculative trading pressure from noise traders helps push up stock prices and creates positive abnormal returns in the short-run for the stocks purchased by institutions (and vice versa for those sold by institutions). Consistent with this 'noise trading' explanation, the short-run return predictive power of both N_Chg and Pct_Chg is found to be stronger for the stocks more prone to speculative trading.

The remainder of the paper is organized as follows. Section I describes the data and variables. Section II documents the institutional ownership anomaly. Section III examines whether the anomaly can be explained by the informational advantage of institutional investors. Section IV explores the alternative 'noise trading' explanation. Section V concludes.

I. Data and the Institutional Ownership Variables

Data used to calculate the institutional ownership variables are obtained from Thomson Financial 13f database. Data on stock returns, stock prices, shares outstanding, and trading volume are from CRSP. Data used to calculate various operating performance measures are from Compustat. The sample period is from January 1982 through December 2006. In each quarter, common stocks (code 10 or 11) are selected with the following criteria: 1) the stock is listed on NYSE, AMEX or NASDAQ; 2) the stock price is no less than \$5 at the end of each quarter (to avoid market microstructure related issues).

As mentioned earlier, two institutional ownership variables are employed in this paper. The first variable, N_Chg, is constructed using the following formula:

$$N\_Chg_{it} = \frac{\#\,of\ inst.holding\ stock\ i\ at\ time\ t - \#\,of\ inst.holding\ stock\ i\ at\ time\ t-1}{\#\,of\ inst.holding\ stock\ i\ at\ time\ t-1} * 100.$$

This variable measures the percentage change in the number of institutions holding stock i during quarter t. The second variable, Pct_Chg, is constructed following Gompers and Metrick (2001) as follows:

$$Pct\_Chg_{it} = \%\ of\ stock\ i\ held\ by\ inst.\ at\ time\ t - \%\ of\ stock\ i\ held\ by\ inst.\ at\ time\ t-1.$$

This variable measures the change in the fraction of shares of stock i owned by institutions during quarter t.

[Insert Table I about here]

Table I reports the summary statistics of these two variables. Panel A provides the average numbers of observations per quarter, means, medians, minimums and maximums of these two variables in various subperiods from 1982 to 2006. [6] It is clear that the number of stocks per quarter is rapidly increasing during 1980s and 1990s, and is more than doubled during our sample period. [7] The trends in the means and medians of N_Chg and Pct_Chg reflect the fact that new institutional investors are entering the market and institutional investors are diversifying their portfolios, especially during the second half of the sample period. Panel A also shows that these two variables are both right-skewed, which is not surprising and suggests that some stocks are experiencing extremely large increases in both the number of institutional investors holding the stocks and the fraction of shares held by institutions, especially during the second half of the sample period.

Panels B and C respectively present the time-series means of the cross-section correlations of these two variables with their respective one-quarter leads and one-quarter lags. The results indicate that N_Chg has virtually no autocorrelation. In contrast, Pct_Chg is negatively autocorrelated – the mean correlation coefficient between Pct_Chg and its lead is -0.14 and that between Pct_Chg and its lag is -0.15 (both are statistically significant at 1% level). Panel D provides the time-series means of the cross-sectional correlations between N_Chg and Pct_Chg. These two variables are positively correlated - the mean correlation coefficient is 0.29 (which is statistically significant at 1% level).

[6] If a firm has no institutional investor (thus no institutional holding) at the beginning of a quarter, but has positive number of institutional investors (thus positive institutional holding) at the end of the quarter, it will have both (N_Chg and Pct_Chg) values missing for the quarter. Pct_Chg value that is gearter that 100% or less than -100% is replaced with missing value.

[7] Untabulated results show that the number of institutions (i.e., 13f filers) per quarter is also steadily and rapidly increasing and is more than quadrupled during the sample period.

II. The Institutional Ownership Anomaly

I examine stock returns for a holding period of three months after the two institutional ownership variables are measured. Specifically, at the end of each quarter (except the quarter ended on March 31st, 1982), I rank stocks based on N_Chg and Pct_Chg respectively, and form 20 decile portfolios based on the decile rankings of these two variables. [8] I then hold the portfolios over the next quarter. I refer to the institutional ownership measurement quarter as the portfolio formation period (denoted by Q0) and the subsequent quarter as the portfolio holding period (denoted by Q1). For each of the 20 decile portfolios, I calculate the (time-series means of) quarterly holding-period returns and t-statistics. The t-statistics are calculated using the Newey-West heteroscedasticity and autocorrelation consistent covariance estimator (Newey and West (1987)).

A. Equal-Weighted Portfolio Results

I first look at the equal-weighted decile portfolio returns, characteristics, and alphas.

1. N_Chg Deciles

[Insert Table II about here]

Table II clearly shows the strong predictive power of N_Chg on next quarter's returns. Raw returns (i.e., Return) are generally increasing from the lowest decile (D1) through the highest decile (D10), albeit non-monotonically. Stocks in D10 significantly outperform those in D1 by 2.88% per quarter with a t-statistic being 4.51; even stocks in the highest three deciles (P70) significantly outperform those in the lowest three deciles (P30) by 1.69% per quarter with a t-statistic being 3.90.

Table II also reports various characteristics of the N_Chg deciles. For each portfolio, I calculate the time-series means of the cross-sectional averages of size (Size), book-to-market (B/M), and momentum (Mom). Size is the log of market capitalization (in $millions)

[8] Since the 13f data I obtained is from 1982 through 2006, I cannot measure N_Chg and Pct_Chg for the first quarter ended on March 31st, 1982.

calculated based on stock price and shares outstanding at the end of Q0. Book-to-market is the log of the ratio of book value of equity to market value of equity at the end of Q0, where the book value of equity is from the most recently reported fiscal quarter (assuming a four-month reporting lag). Momentum is the stock return of the previous six months up to the end of Q0.

It is clear that from D1 through D10, Size is first increasing then decreasing (hump-shape); B/M is generally decreasing; while Mom is monotonically increasing (which is consistent with the findings in extant literature that institutional investors are momentum traders). Although the value effect is unlikely to explain the strong positive relation between N_Chg and future returns, the return predictive power of N_Chg may be driven by small stocks or a mere manifestation of the momentum effect. I next estimate the Jensen's alphas using the Fama-French (1993) 3-factor model and Carhart (1997) 4-factor model.

Table II shows that the 3-factor alphas are generally increasing from D1 through D10, and the difference in 3-factor alphas between D10 and D1 is 3.53% with the t-statistic being 4.77. Thus, controlling for the Fama-French three factors in fact strengthens the return predictive power of N_Chg. The 4-factor alphas show that further controlling for momentum reduces the predictive power of N_Chg. However, N_Chg is still strongly predictive of future stock returns. A long-short strategy that buys D10 and shorts D1 would generate a 4-factor alpha of 2.04% per quarter (8.41% per annum), which is highly statistically significant (the t-statistic as high as 4.48). Even a long-short strategy that longs P70 and shorts P30 would generate a 4-factor alpha of about 1% per quarter with a t-statistic being as high as 3.41.

The raw returns, 3-factor alphas, and 4-factor alphas of the N_Chg decile portfolios are also plotted in Panel A of Figure 1. The figure shows clear upward trends for all of the three curves, which indicate that N_Chg has strong predictive power of future stock returns.

2. Pct_Chg Deciles

I repeat the analyses for the Pct_Chg deciles and the results are reported in Table III and Panel B of Figure 1.

[Insert Table III about here]

It appears that even though there is some positive relation between Pct_Chg and future returns, the relationship is well explained by the Carhart 4-factor model. The 4-factor alpha of D10-D1 is only 0.42% per quarter and is statistically insignificant, and the 4-factor alpha curve is flat across the deciles. In terms of portfolio characteristics, Size is roughly flat across the deciles; B/M is flat at first then decreasing from D1 through D10; Mom is again monotonically increasing from D1 through D10.

B. Value-Weighted Portfolio Results

As the equal-weighted portfolio results may be driven by small stocks, I next look at the value-weighted portfolio results. Table IV reports the portfolio returns, 3-factor alphas and 4-factor alphas for the value-weighted N_Chg and Pct_Chg decile portfolios.

[Insert Table IV about here]

It is clear that the returns and alphas for the value-weighted N_Chg deciles are virtually the same as their equal-weighted counterparts – for example, a zero-investment D10-D1 strategy would generate a 4-factor alpha of 2.04% per quarter (8.41% per annum) with a t-statistic being 4.31; while a P70-P30 strategy would generate a 4-factor alpha of 1% per quarter with a t-statistic being 3.13. The returns and alphas for the value-weighted Pct_Chg deciles are also very similar to their equal-weighted counterparts.

The value-weighted portfolio results suggest that it is quite unlikely that the documented anomaly (i.e., the strong return predictive power of N_Chg) is driven by small stocks.

C. Double-Sorted Portfolio Results

To further ensure that the documented anomaly is not driven by small stocks or just a manifestation of the momentum effect, I next construct double-sorted portfolios. Specifically, at the end of each quarter, I first sort stocks on Size or Mom into Size or Mom quintiles; in each Size or Mom quintile, I then further sort stocks on N_Chg into N_Chg quintiles. Thus, 25 equal-weighted portfolios are formed, and returns and alphas are calculated for each portfolio. [9] The results are reported in Table V (for brevity concern, the tables only report the 4-factor alphas of the double-sorted portfolios).

[Insert Table V about here]

Panel A reports the 4-factor alphas of the 25 portfolios sorted first on Size then on N_Chg. It is clear that in each Size quintile except the largest quintile, 4-factor alphas are generally increasing from the lowest N_Chg quintile (1L) to the highest N_Chg quintile (5H). The 4-factor alphas of the long-short 5H-1L strategy are positive for all of the five Size quintiles (above 1% per quarter for the first four Size quintiles), and are statistically significant (at least at 5% level) for the first four Size quintiles. Therefore, it can be comfortably concluded that the return predictive power of N_Chg exists in at least 80% of the stocks in the market thus is not mainly driven by small stocks.

Panel B reports the 4-factor alphas of the 25 portfolios sorted first on Mom then on N_Chg. In each Mom quintile, 4-factor alphas are generally increasing from the lowest N_Chg quintile (1L) to the highest N_Chg quintile (5H). The 4-factor alphas of the long-short 5H-1L strategy are positive and statistically significant (at least at 5% level) for all of the five Mom quintiles. Therefore, it is clear that the return predictive power of N_Chg is independent of the momentum effect.

In summary, the double-sorted portfolio results confirm that the documented anomaly is not driven by small stocks or momentum. [10]

D. Subsample Results

[9] I do not perform portfolio double-sort first on B/M then on N_Chg, since earlier decile portfolio characteristics results suggest that the value effect cannot account for the documented anomaly.

[10] I also double-sort portfolios first on Size/Mom then on Pct_Chg, and find that the 4-factor alpha of the long-short 5H-1L strategy (i.e., long the highest Pct_Chg quintile and short the lowest Pct_Chg quintile) are not significantly different from zero in each Size/Mom quintile. These results are not reported for brevity.

Next, I divide the full sample into two subsamples to see whether the institutional ownership anomaly is robust in different subsamples. The first subsample covers the period from 1982 to 1994; while the second subsample covers the period from 1995 to 2006. I construct equal-weighted decile portfolios based on the two institutional ownership variables and calculate portfolio returns and alphas for each subsample. [11] The results are reported in Table VI and Table VII.

[Insert Table VI about here]

Table VI shows that N_Chg has very strong return predictive power during 1982-1994. For example, during this period, a long-short D10-D1 strategy based on the N_Chg deciles would generate a 4-factor alpha of 2.55% per quarter with a t-statistic being as high as 4.65. Pct_Chg appears to have no return predictive power during this period.

[Insert Table VII about here]

Table VII shows that N_Chg still has return predictive power during 1995-2006, although its predictive power is weaker in this second period than in the first period. For example, during this second period, a long-short D10-D1 strategy based on the N_Chg deciles would generate a 4-factor alpha of 1.38% per quarter with a t-statistic being 2.09. Pct_Chg again appears to have no return predictive power.

The subsample results suggest that N_Chg has robust return predictive power in both subsamples, while Pct_Chg appears to have no predictive power in either subsample.

E. The Performance of the Zero-Investment D10-D1 Strategies over Time

As a robustness check, I explore the performance over time of the two Zero-Investment D10-D1 strategies that long D10 and short D1, with the equal-weighted decile portfolios formed by sorting on past N_Chg and Pct_Chg respectively. I obtain the quarterly return series for both (zero-investment) strategies and compound the quarterly returns into annual

[11] Value-weighted subsample results are virtually the same as equal-weighted results and are not reported for brevity.

return each year, and plot the two time-series of annual returns in Figure 2.

Without surprise, the two annual return time-series are positively correlated, with the zero-investment strategy constructed on the N_Chg deciles performing much better than that based on the Pct_Chg deciles (as the N_Chg annual return time-series lies almost entirely above the Pct_Chg time series) – it generates positive annual returns in twenty-two of the twenty-five years in the sample period (the returns are negative but almost zero in 1992 and 1997; the return is -16.8% during the NASDAQ crash in 2001), and generates positive annual returns above 10% in fourteen of the twenty-five years.

F. A Waiting Period of Two Months Added before Portfolio Formation

To see whether the documented anomaly is tradable, I further add a two-month waiting period between the portfolio formation period (Q0) and the portfolio holding period (Q1).[12] Specifically, at the end of each Q0, I rank stocks based on N_Chg and Pct_Chg respectively, wait for two months, and then form 20 equal-weighted decile portfolios based on the decile rankings of the two variables and hold the portfolios over the next three months. The holding-period portfolio returns, 3-factor alphas and 4-factor alphas are reported in Table VIII.

[Insert Table VIII about here]

Table VIII shows that N_Chg still has strong return predictive power even after controlling a two-month waiting period. For example, a zero-investment D10-D1 strategy based on the N_Chg deciles would generate a 4-factor alpha of 0.97% per quarter (3.94% per annum) with a t-statistic being 2.25. Thus, such a strategy is fully tradable.[13]

G. Long-Run Portfolio Returns

Finally, I look at the long-run return performance of the portfolios formed based on the

[12] Since the 13-f filers are mandated to file their reports to the SEC within 45 days from the end of a calendar quarter (Rule 13f-1 under the Securities Exchange Act of 1934), information needed to calculate the institutional ownership variables may not be immediately available to the investing public at the end of the portfolio formation period (Q0).

[13] The (untabulated) value-weighted results (controlling a two-month waiting period) are virtually the same as the reported equal-weighted results.

rankings of past N_Chg and Pct_Chg. Specifically, at the end of each Q0, I rank stocks based on N_Chg and Pct_Chg and form 10 equal-weighted quintile portfolios. For each of the next eight quarters after portfolio formation, I then calculate the quintile portfolio returns and their respective Newey-West t-statistics. The results are reported in Table IX and plotted in Figure 3. For brevity, I only report the portfolio returns of the highest quintiles (5H) and the lowest quintiles (1L), the 5H-1L return differences, and the New-West t-statistics of the 5H-1L return differences.

[Insert Table IX about here]

Table IX and Figure 3 clearly show that the 5H-1L future return differences demonstrate the same interesting reversal pattern for the two institutional ownership variables – the future return differences are positive but decreasing in the first three quarters after Q0 (significantly positive in Q1 and Q2 for N_Chg; insignificant for Pct_Chg), become negative since Q4, and even become significantly negative in Q5 and Q6 before finally narrowing down in Q7 and Q8. This interesting reversal pattern clearly shows that the documented anomaly is only short-run in nature – the relations start to reverse after two quarters.

The documented long-run return reversal clearly shows that the optimal portfolio holding period should be no more than three quarters for the zero-investment long-short strategies based on the institutional ownership variables. However, based on existing empirical evidences (e.g., Carhart (1997), Wermers (2000), and Jin (2004)), San (2007) estimates that the average holding period for institutions is fifteen months (or even longer). From the documented long-run return reversal result, it is clear that the return difference between the stocks purchased by institutions and those sold by institutions already becomes significantly negative in the fifth quarter after the initial institutional trading has been made. Thus, the result can help explain San (2007)'s finding that compared to individuals, institutions on average realize inferior returns from their stock trading.

As a summary of Section II, I document evidence that percentage changes in the number of institutional investors in a firm's ownership structure (N_Chg) strongly positively predict short-run (especially next quarter's) stock returns. This return predictive power of N_Chg is very robust - it is independent of size, value, and momentum; it exists in both the full sample period and subperiods; it exists even when a two-month waiting period is added before portfolio formation. Consistent with Gompers and Metrick (2001), I also document an insignificant relation between changes in the fraction of shares owned by institutions (Pct_Chg) and next quarter's stock returns. Furthermore, I find similar long-run reversal patterns for the return differences between the highest quintiles and the lowest quintiles sorting on the two institutional ownership variables, which suggest that the institutional ownership anomaly is short-run in nature.

III. Is the Anomaly Information Driven?

It is tempting to attribute the documented institutional ownership anomaly to the informational advantage of institutional investors. An implied assumption behind this explanation is that institutional investors on average have informational advantage over individual investors. In this section, I first test the hypothesis that the documented anomaly is driven by the superior information of institutional investors. I then go a step further and test the more fundamental hypothesis that institutional investors are (on average) better informed than individual investors. Along the way of testing the information-based explanation, I also examine whether other explanations (mentioned in the introduction) can account for the anomaly or not.

A. Fama-Macbeth Regression Results

I perform quarterly Fama-MacBeth regressions of next quarter's return (i.e., return in Q1) on the two institutional ownership variables (measured at the end of Q0) respectively, with various control variables.

1. N_Chg Regression Results

The results of Fama-Macbeth regressions of next quarter's return on N_Chg are reported in Table X. [14]

[Insert Table X about here]

Model 1 is the univariate result with only N_Chg as the independent variable. It is clear that without any control, N_Chg is significantly positively related to next quarter's return (with a Newey-West t-statistic being 2.44), which confirms the earlier result that the raw returns of the N_Chg decile portfolios are generally increasing from D1 through D10.

Next, I control for Beta, Size and B/M in Model 2, and further control for Mom in Model 3. Beta is estimated in the manner of Fama and French (1992) at the end of Q0. Size, B/M and Mom (described in the last section) are also measured at the end of Q0. The result of Model 2 shows that, after controlling for Beta, Size and B/M, the coefficient of N_Chg is more than doubled – doubling the number of institutional investors in a firm's ownership structure is (on average) related to a 1.24% increase in next quarter's stock return of the firm (t-statistic also increases to 3.47). Further controlling for momentum in Model 3 produces very similar result to that of Model 2. Thus, the regression results from Model 2 and Model 3 are consistent with the prior portfolio-sorting results, and further confirm that the return predictive power of N_Chg is independent of size, book-to-market and momentum.

To correct for any spurious relation caused by possible autocorrelation in the institutional ownership variables (as suggested by Lehavy and Sloan (2008)), I further control for the one-quarter lag and one-quarter lead of N_Chg in Model 4 and Model 5. [15] It is clear that the coefficient of Lead_N_Chg is positive and highly significant in both Model 4 and Model 5,

[14] The coefficient estimates of N_Chg, its one-quarter lead and its one-quarter lag are all multiplied by 100 for the ease of demonstration and interpretation.

[15] Lehavy and Sloan (2008) show that without controlling for the autocorrelation in the changes in the breadth of institutional ownership (i.e., ΔBreadth), ΔBreadth appears to be (significantly) positively related to future stock returns. However, when the one-quarter lead and one-quarter lag of ΔBreadth are added to the regression model, ΔBreadth flips sign and becomes (significantly) negatively related to next quarter's returns.

suggesting that N_Chg is strongly positively related to contemporaneous return. [16] More importantly, compared to the univariate result of Model 1, after controlling for the lead and lag of N_Chg, the coefficient of N_Chg is more than doubled to 1.45 in Model 4 (with the t-statistic being 3.18); while compared to Model 3, controlling for its lead and lag more than triples the coefficient of N_Chg to 3.45 in Model 5 (with t-statistic more than doubled to 7.18). The results in Model 4 and Model 5 confirm that the return predictive power of N_Chg is not spurious, but is in fact robust and strong.

To test the hypothesis that the short-run return predictive power of N_Chg is mainly driven by the informational advantage of institutional investors, I further control for current and future earnings news. Corporate earnings are (arguably) the most important determinant of stock returns. If institutional investors are better informed than others about the innovations in corporate earnings and if this informational advantage is the driver of the return predictive power of N_Chg, controlling for current and future earnings news should eliminate (or at least reduce) this predictive power.

I measure current earnings news, E_Chg, as the seasonal change in earnings before extraordinary items (from the one-year-ago quarterly value) scaled by average total assets for the fiscal quarter ended in Q0; I measure future earnings news, Lead_E_Chg, as the lead-one-quarter value of E_Chg. Both variables are measured in percentage points. The result is reported in Model 6 of Table X. Without surprise, both E_Chg and Lead_E_Chg are highly positively related to the stock return in Q1 – for example, a one-percentage-point increase in E_Chg is on average related to a 38-basis-point increase in the stock return of Q1 (with the t-statistic being as high as 11.89); while a one-percentage-point increase in Lead_E_Chg is related to a 66-basis-point increase in Q1's return (with the t-statistic being 11.93). However, after controlling for current and future earnings news, the coefficient of

[16] This is not surprising as extant literature find that institutional investors are momentum traders. For example, Cai and Zheng (2004) document a strong contemporaneous relation between the intensity of institutional trading and stock returns; they further find that stock returns Granger-cause institutional trading (especially purchases).

N_Chg in Model 6 is 3.39 (and the t-statistic even increases to 7.45), which is virtually the same as that in Model 5. Thus, the evidence is inconsistent with the information-based hypothesis.

Ang, Hodrick, Xing, and Zhang (2006) document a significant inverse relation between idiosyncratic volatility (IV) and future stock returns. Jiang, Xu and Yao (2009) show that IV contains information about (thus forecasts) both next quarter's and next year's corporate earnings and earnings shocks, and that the return predictive power of IV comes from this information content. Since institutional investors are traditionally viewed as sophisticated investors, they may be able to obtain an informational advantage over individual investors through better decoding the implicit information contained in IV. Therefore, I further add IV as a control variable, and the result is reported in Model 7 of Table X. IV is estimated in the manner of Ang, Hodrick, Xing, and Zhang (2006) and is in percentage point.[17] As expected, IV is strongly negatively related to the stock return in Q1 – a one-percentage-point increase in IV is on average related to a 53-basis-point reduction in Q1's return (with the t-statistic being -2.99). However, after this additional control of IV in Model 7, there is virtually no change to the coefficient estimate of N_Chg, which is 3.32 with the t-statistic being as high as 7.62. The evidence is again at odds with the information-based hypothesis.

Therefore, the evidence does not support the hypothesis that the informational advantage of institutions drives the return predictive power of N_Chg.

2. Pct_Chg Regression Results

The Fama-Macbeth regression results of next quarter (Q1)'s return on current quarter (Q0)'s Pct_Chg are reported in Table XI.

[17] Specifically, at the end of each Q0, I estimate the following Fama-French 3-factor regression equation for each stock: $r_t = \alpha + \beta_1 HML_t + \beta_2 SMB_t + \beta_3 r_{m,t} + \varepsilon_t$. where r_t is the daily stock return, HML_t and SMB_t are the daily Fama-French book-to-market and size factors, and $r_{m,t}$ is the daily CRSP value-weighted index return. The idiosyncratic volatility measure, IV, is the standard deviation of the residuals (ε_t) from this regression. In order to accurately estimate IV, a stock needs to have at least 44 daily return observations in CRSP during the measurement quarter (Q0).

[Insert Table XI about here]

Model 1, Model 2 and Model 3 show that Pct_Chg has little return predictive power either in the univariate analysis or after controlling for the common factor exposures, which is consistent with the prior findings from the portfolio-sorting approach. Interestingly, after controlling for beta, size, book-to-market and momentum, Pct_Chg becomes negatively related to future stock return at 10% significance level (Model 3). Model 4 and Model 5 control the negative autocorrelation in Pct_Chg by adding the one-quarter lag and one-quarter lead of Pct_Chg into the regressions (as Panel C of Table I shows that Pct_Chg is negatively autocorrelated).

As expected, Lead_Pct_Chg is highly positively related to Q1's return in Model 4. Surprisingly, Model 4 reveals that after controlling for the negative autocorrelation in Pct_Chg, Pct_Chg itself (and Lag_Pct_Chg as well) becomes strongly positively related to Q1's stock return. The coefficient estimate of Pct_Chg is 0.11 with its t-statistic being as high as 5.20, which means a one-percentage-point increase in institutions' share ownership would on average relate to an 11-basis-point increase in next quarter's stock return. Controlling for the common factor exposures brings no change to this strong return predictive power of Pct_Chg – the coefficient estimate of Pct_Chg is 0.10 with an even higher t-statistic (6.29) in Model 5. Thus, the return predictive power of Pct_Chg is independent of size, book-to-market, and momentum.

This finding of a strong short-run return predictive power of Pct_Chg after controlling for the negative autocorrelation in Pct_Chg implies that the apparent absence of return predictive power in Pct_Chg, documented earlier in the paper and in current literature (e.g., Gompers and Metrick (2001)), is driven by the fact that Pct_Chg is negatively autocorrelated and is also highly positively correlated with contemporaneous return. In other words, the strong positive correlation between Pct_Chg and contemporaneous stock return and the negative autocorrelation in Pct_Chg bring in a negative relation between Pct_Chg and future return, which offsets the positive return predictive power of Pct_Chg in its own and makes it appear that Pct_Chg has no significant relation with future stock return. This finding can be contrasted with Yan and Zhang (2009). Without controlling for the autocorrelation in changes in institutions' share ownership, Yan and Zhang (2009) find that only the changes in short-term institutions (i.e., institutions with high turnover)' share ownership can predict future stock returns. This paper shows that after controlling for the negative autocorrelation in Pct_Chg, the changes in all institutions (i.e., not only short-term institutions)' share ownership in a firm strongly predict the short-run future stock returns of the firm.

To test whether the short-run return predictive power of Pct_Chg can be explained by the informational advantage of institutional investors, I further control for current and future earnings news in Model 6, and add IV as an additional control in Model 7. The results show that adding these controls brings virtually no change to the strong return predictive power of Pct_Chg – the coefficient of Pct_Chg is 0.09 in both models with the t-statistic being 6.24 in Model 6 and 5.66 in Model 7. Thus, the evidence is again inconsistent with the information-based hypothesis.

As a summary of this subsection, the Fama-Macbeth regression results confirm that N_Chg has strong and robust predictive power of next quarter's stock return. The regression results also disclose that after controlling for its negative autocorrelation, Pct_Chg in fact also has strong short-run return predictive power. Furthermore, the evidence does not support the hypothesis that the informational advantage of institutional investors is the driver behind the strong return predictive power of N_Chg and Pct_Chg. [18]

B. Do Institutions Have Informational Advantage?

[18] Extant literature document that liquidity and accounting accruals also have cross-sectional predictive power of future stock returns. As a robustness check, at the end of each Q0, I estimate the liquidity measure, LIQ, in the manner of Pastor-Stambaugh (2003) and the discretionary accruals measure, DA, in the manner of Chan, Chan, Jegadeesh and Lakonishok (2006) and Sloan (1996) (assuming a 4-month reporting lag), and add LIQ and DA as additional control variables in the Fama-Macbeth regressions. The results remain virtually unchanged given these additional controls. They are not reported for brevity concern.

As mentioned earlier, conventional wisdom views institutions as sophisticated investors who on average possess informational advantage over individuals. In this subsection, I directly test the hypothesis that institutions are on average better informed than individuals.

First, I examine whether institutions on average have superior information about future innovations in corporate earnings, by comparing the seasonal earnings growth of stocks purchased by institutions and stocks sold by institutions before and after institutional trading is made. Specifically, at the end of each quarter, I rank stocks based on N_Chg and Pct_Chg respectively and form 10 equal-weighted quintile portfolios. For each quintile portfolio, I then calculate the time-series mean of the portfolio seasonal earnings growth rate for each of the four quarters before portfolio formation (i.e., Q_3, Q_2, Q_1 and Q0) and each of the eight quarters after portfolio formation (i.e., Q1, Q2, Q3, Q4, Q5, Q6, Q7 and Q8). [19] Seasonal earnings growth rate of a firm in a quarter is measured as the firm's seasonal change in earnings before extraordinary items (from the one-year-ago quarterly value) for the quarter scaled by its average total assets. The measure is industry-demedianed (i.e., subtracted by the corresponding two-digit SIC industry median) to control for potential industry effect, and is reflected in percentage term.[20] The result is reported in Table XII and further plotted in Figure 4. For brevity I only report the average seasonal earnings growth rates for the highest quintiles (5H) and the lowest quintiles (1L), the 5H-1L seasonal earnings growth differences, and the Newey-West t-statistics of the 5H-1L differences.

[Insert Table XII about here]

Table XII and Figure 4 reveal some interesting results. Stocks purchased by institutions (the 5H quintiles) demonstrate positive and increasing seasonal earnings growth but only up

[19] To avoid the complexity induced by matching calendar quarter with fiscal quarter, I only include firms with fiscal year ended in December in the analysis.

[20] To remove coding errors and reduce the impact of outliers, I first winsorize the seasonal earnings growth rate measure in the dataset by replacing extreme values (below 1 percentile or above 99 percentile) with the respective 1 percentile or 99 percentile values in each quarter, then use the winsorized data to calculate the average seasonal earning growth for the quintile portfolios before and after portfolio formation. The same winsorization treatment is also applied to the other two measures (which are discussed later in this subsection) – seasonal net operating cash flow growth and seasonal sales growth.

to Q_1 (i.e., the quarter before the portfolio formation quarter Q0); Starting from Q0 (the quarter when institutional purchase is made), the seasonal earnings growth of these stocks reverses trend and is declining, and quickly becomes negative (in Q2). In contrast, stocks sold by institutions (the 1L quintiles) show negative and declining seasonal earnings growth but only up to Q1 or Q2; the seasonal earnings growth of these stocks then reverses trend and is increasing, and even becomes positive in later quarters (Q7 and Q8). More importantly, the seasonal earnings growth differences between stocks purchased by institutions (the 5H quintiles) and those sold by institutions (the 1L quintiles) are significantly positive and increasing before institutional trading, peak at around the timing of institutional trading, then reverse trend and are quickly declining afterwards, and even become significantly negative in the later quarters (since Q5).

It is without surprise to see a reversal in seasonal earnings growth, as standard economics arguments (e.g., Stigler (1963)) imply that, in a competitive environment, profitability demonstrates mean reversion. Fama and French (2000) also show corroborating evidence that changes in profitability and changes in earnings are indeed mean reverting. What is really surprising is the finding that the reversal occurs at around the timing of institutional trading. If institutional investors indeed (on average) possessed superior information over individual investors about future innovations in corporate earnings, we would expect to see an increasingly upward sloping trend (before the reversal finally occurs) in the seasonal earnings growth difference between stocks purchased by institutions and those sold by institutions after institutional trading has been made, and would never expect to see such a dramatic reversal in seasonal earnings growth difference at the timing of institutional trading. Therefore, the evidence is against the hypothesis that institutions have informational edge (about future corporate earnings innovations) over individuals.

This finding, however, echoes the earlier finding of a long-run reversal in return difference between stocks purchased by institutions and those sold by institutions documented in Section II. As mentioned earlier, the average holding period of institutions is five quarters (or even longer), from Figure 4 it is clear that in Q5 the seasonal earnings growth difference between stocks purchased by institutions and those sold by institutions has become (significantly) negative and is almost at the bottom of the curve. In contrast, in Q0 (i.e., in the quarter when institutional purchase and sale are made), the seasonal earnings growth difference is highly positive and is almost at the peak of the curve. Thus, in terms of corporate earnings innovations, institutions appear to buy high and sell low, which may also help explain San (2007)'s finding that institutions realize inferior returns compared to the returns realized by individuals.

As one might argue that corporate earnings are subjected to manipulation by corporate managers, I next examine whether institutions have superior information about future innovations in corporate net operating cash flow (OCF), by comparing the seasonal net OCF growth of stocks purchased by institutions and stocks sold by institutions before and after institutional trading. The result is reported in Table XIII and plotted in Figure 5. Seasonal net OCF growth rate of a firm in a quarter is measured as the firm's seasonal change in net OCF (from the one-year-ago quarterly value) for the quarter scaled by its average total assets. The measure is also industry-demedianed and reflected in percentage term.

[Insert Table XIII about here]

Table XIII and Figure 5 clearly show that the seasonal net OCF growth differences between stocks purchased by institutions (the 5H quintiles) and those sold by institutions (the 1L quintiles) demonstrate a similar reversal pattern - the seasonal net OCF growth differences are significantly positive and increasing before institutional trading, peak at the timing of institutional trading, then reverse trend and are quickly declining afterwards, and are not significantly different from zero in the later quarters. Thus, in terms of future corporate operating cash flow innovations, institutional investors also appear to buy high and sell low.

As a robustness check, I further examine whether institutions have superior information about future corporate sales innovations. The result is reported in Table XIV and plotted in Figure 6. Seasonal sales growth rate of a firm in a quarter is measured as the firm's net sales of the quarter minus its net sales of the corresponding one-year-ago quarter then divided by its net sales of the corresponding one-year-ago quarter. The measure is again industry-demedianed and reflected in percentage points.

[Insert Table XIV about here]

As can be seen, there is a similar reversal in the seasonal sales growth differences between stocks purchased by institutions and those sold by institutions after institutional trading. Thus, institutions also do not appear to have superior information about future corporate sales innovations.

The surprising findings of this subsection can also serve as evidence against the aforementioned 'corporate governance' explanation (discussed in the introduction) to the documented institutional ownership anomaly. If the 'corporate governance' hypothesis was true, one would expect an accelerated improvement in corporate operating performance after institutional purchase is made (since the hypothesis assumes that institutional investors exert monitoring to the firm's management thus reduce agency costs of the firm), rather than an abrupt reversal in operating performance innovations.

Finally, as one might argue that institutions may possess superior information in picking undervalued stocks, which drives the documented short-run positive return predictive power of N_Chg and Pct_Chg, I further examine whether stocks purchased by institutions are indeed undervalued in the market or not. I use Tobin's Q as a measure of market valuation, and perform Fama-Macbeth regressions of Q on contemporaneous N_Chg and Pct_Chg respectively. I include Log(assets), Mom, Lag_Q and industry dummies as controls. [21] Tobin's Q is calculated as book value of assets minus book value of common equity minus deferred taxes plus market value of common equity and then divided by book value of assets, and is measured at the end of current quarter (Q0) with the relevant accounting information being from the most recently reported fiscal quarter (assuming a four-month reporting lag). [22] Lag_Q is the one-quarter lag of Q. Log(assets) is the log of book value of assets. The results are reported in Table XV.

[Insert Table XV about here]

It is clear that N_Chg and Pct_Chg are both (significantly) positively associated with contemporaneous Q. For example, doubling the number of institutional shareholders is associated with a 22% premium in valuation, with the t-statistic being 5.34; while a one-percentage-point increase in institutional share ownership is related to a 1% evaluation premium, with the t-statistic being 4.84. Thus, the evidence is at odds with the hypothesis that institutions possess superior information in picking undervalued stocks. The evidence also does not support the aforementioned 'omitted risk' hypothesis that changes in institutional ownership are associated with some unknown risk factor, thus investors lower their valuations of firms experiencing higher N_Chg and Pct_Chg to demand a risk premium.

The short-run positive return predictive power of N_Chg and Pct_Chg also is unlikely to be driven by persistent institutional demand, as we would expect positive autocorrelation in both N_Chg and Pct_Chg if the 'persistent institutional demand' explanation was true. However, the paper shows that there is virtually zero autocorrelation in N_Chg and there is a negative autocorrelation in Pct_Chg.

IV. An Alternative Explanation to the Anomaly

[21] I use the Fama-French 10-industry classification, which is obtained from Prof. Kenneth French's website. I thank Prof. French for providing this data on his website.

[22] To remove coding errors and reduce the impact of outliers, in every quarter, I also winsorize Q by replacing extreme values (below 1 percentile or above 99 percentile) with its respective 1 percentile or 99 percentile value.

An alternative potential explanation to the documented institutional ownership anomaly is that noise traders in the market erroneously view institutions as (on average) possessing superior information and view institutional trading as conveying valuable information. Thus, the noise traders follow suit and trade on 'noise' (Black (1986)). The speculative trading pressure from noise traders thus helps push up stock prices and creates positive abnormal returns in the short-run for the stocks purchased by institutions (and vice versa for the stocks sold by institutions). Given that noise traders' holding period is short (alternatively, given that the reversal in corporate operating performance innovations after institutional trading unfolds), their later liquidation of stock holdings will then exert a downward pressure to the prices of these stocks, which results in a return reversal documented in Section II.

If the above 'noise trading' explanation is true, the short-run return predictive power of N_Chg and Pct_Chg should be stronger for the stocks more prone to speculative trading. This is a testable implication. Baker and Wurgler (2006, 2007) show evidence that the stocks more prone to speculation also tend to be more sensitive to investor sentiment. Therefore, I use the BW sentiment beta (which quantifies the comovement of stock returns with the changes in investor sentiment) of a stock as a proxy for the degree to which the stock is affected by speculative trading, and perform Fama-MacBeth regressions of next quarter's return (i.e., return in Q1) on the interaction term between sentiment beta and N_Chg or that between sentiment beta and Pct_Chg (all measured in Q0), with various control variables. The 'noise trading' explanation to the institutional ownership anomaly predicts that the regression coefficient of the interaction term should be positive and significant.

In order to reduce the noise in measuring the sentiment beta of individual stock, a portfolio approach similar to the one in Fama and French (1992) is employed. Specifically, at the end of December in each year, I perform time-series regression of monthly return on Baker and Wurgler (2007)'s index of sentiment changes (with macro-effect removed) and

CRSP value-weighted index return for each stock over the past 60 months (24 months at least) to obtain its pre-ranking sentiment beta (i.e., the regression coefficient of the sentiment change index). [23] [24] I then independently sort stocks into size and pre-ranking sentiment beta deciles (based on NYSE decile breakpoints) to form 100 size-sentiment beta portfolios and hold them over the next 12 months. For each of the 100 portfolio, I then perform time-series regression of the monthly equal-weighted portfolio return on the BW sentiment change index (with macro-effect removed) and CRSP value-weighted index return over the entire sample period to estimate its full-sample sentiment beta. The variable, sentiment beta, used in the FM regressions is the full-sample sentiment beta of the size-sentiment beta portfolio which a stock belongs to at the beginning of the year (which Q0 belongs to). The regression results are reported in Table XVI. In each regression model of Table XVI, Beta, Size, B/M and Mom are also included as control variables, but they are omitted from the table for brevity concern.

[Insert Table XVI about here]

Table XVI shows that, in all of Model 1, Model 2 and Model 3, the coefficient of sentiment beta is insignificant, which means that sentiment beta itself has no return predictive power, while the coefficient of N_Chg is positive and significant (consistent with previous results in Table X). More interestingly, consistent with the implication of the 'noise trading' explanation, the regression coefficient of the interaction term between sentiment beta and N_Chg (i.e., Sentiment Beta*N_Chg) is positive and statistically significant at (at least) 5% level in all of the three models. The models imply that combining an increase of a stock's sentiment beta by 0.01 and doubling the number of institutional investors holding the stock is

[23] The Baker and Wurgler (2007) index of sentiment changes is the first principal component of the changes in six proxies of investor sentiment (from January 1966 through December 2005) used by Baker and Wurgler (2006): the closed-end fund discount, detrended log NYSE turnover, the number of IPOs, the first-day return on IPOs, the dividend premium, and the equity share in new issues, each standardized and with the effect of macroeconomic conditions removed (by regressing each proxy on a set of macroeconomic indicators and obtain the residuals). When measuring the changes in sentiment proxies, turnover, the first-day return on IPOs and the dividend premium are lagged 12 months. The BW index of sentiment changes is standardized to have zero mean and unit variance. The data are obtained from Prof. Jeffrey Wurgler's website.

[24] I thank Prof. Jeffrey Wurgler for generously providing the data on his website.

(on average) related to an additional 2% to 2.5% increase in next quarter's stock return of the firm.

Similarly, the regression coefficient of the interaction term between sentiment beta and Pct_Chg (i.e., Sentiment Beta*Pct_Chg) is positive in all of Model 4, Model 5, and Model 6, and is statistically significant at 10% level in both Model 4 and Model 6 (it is marginally insignificant in Model 5). Implied by the models, the combination of an increase of a stock's sentiment beta by 0.01 and a ten-percentage-point increase in institutions' share ownership of the stock is (on average) related to an increase in next quarter's stock return of about 1%. Consistent with previous results in Table XI, the coefficient of Pct_Chg is negative and significant in Model 4 (without controlling for the autocorrelation in Pct_Chg), and is positive and significant in Model 5 and Model 6 (when the autocorrelation in Pct_Chg is controlled). The coefficient of sentiment beta is again insignificant in all of the three models.

Overall, the regression results in Table XVI confirm that the short-run return predictive power of both N_Chg and Pct_Chg is stronger for the stocks more subjected to speculative trading, which is consistent with the implication of the 'noise trading' explanation to the anomaly. If noise traders' average holding period is shorter than 3 quarters, based on the result documented in Table IX and Figure 3, they will make an abnormal trading profit and realize returns superior to those realized by institutions. This paper's findings then support the theoretical implications of De Long, Shleifer, Summers, and Waldmann (1990) that noise traders can exist in capital market in the long run, earn a higher expected return than that of sophisticated investors, and have significant effects on asset prices.

V. Conclusion

This paper documents that percentage change in the number of institutional investors (N_Chg) has strong predictive power of short-run future stock return – a long-short strategy that buys the largest N_Chg decile and shorts the smallest decile each quarter would generate

Carhart 4-factor alpha of 2.04% per quarter (8.41% per annum) between 1982 and 2006. This return predictive power is both robust and tradable. After the negative autocorrelation in change in the fraction of shares of a stock owned by institutions (Pct_Chg) is controlled, Pct_Chg also strongly positively predicts short-run future stock returns. However, the return predictive power of N_Chg and Pct_Chg is short-run in nature – the relations start to reverse after two quarters.

Contrary to conventional wisdom, the short-run return predictive power of N_Chg and Pct_Chg is not driven by superior information of institutional investors, as controlling for corporate earnings news and idiosyncratic volatility does not eliminate or even reduce the predictive power. In fact, the paper documents dramatic trend reversals in corporate seasonal earnings growth, seasonal cash flow growth and seasonal sales growth around the timing of institutional trading, which suggest that institutional investors (on average) have no informational advantage over individual investors regarding future innovations in corporate operating performance. The finding that N_Chg and Pct_Chg are both significantly positively associated with contemporaneous Tobin's Q also casts doubt on the hypothesis that the institutional ownership anomaly is driven by institutions possessing superior information in picking undervalued stocks.

This paper proposes an alternative potential explanation to the documented anomaly – the anomaly might be driven by speculative trading of noise traders. Consistent with this 'noise trading' explanation, the short-run return predictive power of both N_Chg and Pct_Chg is found to be stronger for the stocks more prone to speculative trading.

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Table I
Summary Statistics of Institutional Ownership Variables

Table I, Panel A, reports the summary statistics of N_Chg and Pct_Chg during various subperiods from 1982 to 2006. N is the average number of observations per quarter during the subperiod. Panel B reports the time-series average of the cross-sectional correlations among N_Chg, its one-quarter lead, and its one-quarter lag during all subperiods. Panel C reports the time-series average of the cross-sectional correlations among Pct_Chg, its one-quarter lead, and its one-quarter lag during all subperiods. Panel D reports the time-series average of the cross-sectional correlations between N_Chg and Pct_Chg during all subperiods.

Panel A: Descriptive Statistics					
	N_Chg (%)				
Period	N	Mean	Median	Min	Max
82-84	1749	12.85	0	-96.43	26000.00
85-89	2840	14.34	0	-95.652	33500.00
90-94	3163	10.73	0	-96.154	25500.00
95-99	4618	30.42	0	-94.737	32400.00
00-04	4052	30.85	1.49	-88.889	97800.00
05-06	4126	25.57	0.93	-92.391	33450.00
	Pct_Chg (%)				
Period	N	Mean	Median	Min	Max
82-84	1744	0.64	0.40	-85.84	86.29
85-89	2824	0.42	0.31	-83.19	86.46
90-94	3130	0.44	0.12	-95.80	84.82
95-99	4562	0.44	0.13	-99.82	90.20
00-04	4039	0.95	0.38	-97.25	98.75
05-06	4114	1.16	0.54	-90.48	95.09

Table I
Summary Statistics of Institutional Ownership Variables (continued)

Panel B: Correlation of Lag_N_Chg, N_Chg, Lead_N_Chg

	Lead_N_Chg	N_Chg	Lag_N_Chg
Lead_N_Chg	1		
N_Chg	0.01	1	
Lag_N_Chg	0.01	0.00	1

Panel C: Correlation of Lag_Pct_Chg, Pct_Chg, Lead_Pct_Chg

	Lead_Pct_Chg	Pct_Chg	Lag_Pct_Chg
Lead_Pct_Chg	1		
Pct_Chg	-0.14	1	
Lag_Pct_Chg	-0.01	-0.15	1

Panel D: Correlation of N_Chg and Pct_Chg

	N_Chg	Pct_Chg
N_Chg	1	
Pct_Chg	0.29	1

Table II
Equal-Weighted Portfolios Sorted by N_Chg

Table II reports the average portfolio-holding-quarter (Q1) portfolio returns (Return), alphas of the Fama-French (1993) 3-factor model and the Carhart (1997) 4-factor model, and t-statistics, of equal-weighted decile portfolios formed at the end of each portfolio formation quarter (Q0) based on N_Chg. The time-series means of N_Chg and various portfolio characteristics, including size (Size), book-to-market (B/M), and momentum (Mom) are also reported. Size is the log of market capitalization (in $millions) calculated based on stock price and shares outstanding at the end of Q0. B/M is the log of the ratio of book value of equity to market value of equity, where the book value of equity is from the most recently reported fiscal quarter assuming a four-month reporting lag. Mom is the stock return of the previous six months up to the end of Q0. Returns and alphas are in percentage points. The Newey-West t-statistics are computed with a one-quarter lag.

Decile of N_Chg	N_Chg (%)	Size	B/M	Mom	Return	3-Factor Alpha	4-Factor Alpha
D1(L)	-23.42	4.44	-0.59	-0.60	2.56	-1.57 (-2.95)	-1.14 (-2.74)
D2	-9.14	5.25	-0.59	-0.20	3.44	-0.72 (-2.02)	-0.23 (-0.92)
D3	-4.12	5.62	-0.65	2.84	4.06	-0.32 (-0.86)	0.19 (0.67)
D4	-1.41	6.02	-0.72	4.61	3.16	0.02 (0.04)	0.30 (1.07)
D5	1.35	6.70	-0.81	7.66	2.77	-0.09 (-0.29)	-0.03 (-0.12)
D6	4.00	6.63	-0.82	10.65	3.87	-0.44 (-1.16)	-0.45 (-1.27)
D7	7.40	6.25	-0.83	14.67	4.24	0.10 (0.38)	-0.02 (-0.09)
D8	12.36	5.70	-0.82	18.36	4.72	0.80 (3.70)	0.48 (2.32)
D9	21.85	5.15	-0.88	26.13	4.76	0.95 (3.26)	0.24 (1.18)
D10(H)	221.65	4.61	-1.12	44.35	5.44	1.96 (4.25)	0.89 (2.64)
D10-D1	245.07	0.17	-0.53	44.94	2.88	3.53	**2.04**
t-Stats	(11.06)	(3.18)	(-13.17)	(11.96)	(4.51)	(4.77)	**(4.48)**
P70-P30	97.79	0.07	-0.33	28.98	1.69	2.12	0.99
t-Stats	(13.15)	(1.28)	(-11.98)	(13.26)	(3.90)	(3.86)	(3.41)

Table III
Equal-Weighted Portfolios Sorted by Pct_Chg

Table III reports the average portfolio-holding-quarter (Q1) portfolio returns (Return), alphas of the Fama-French (1993) 3-factor model and the Carhart (1997) 4-factor model, and t-statistics, of equal-weighted decile portfolios formed at the end of each portfolio formation quarter (Q0) based on Pct_Chg. The time-series means of Pct_Chg and various portfolio characteristics, including size (Size), book-to-market (B/M), and momentum (Mom) are also reported. Size is the log of market capitalization (in $millions) calculated based on stock price and shares outstanding at the end of Q0. B/M is the log of the ratio of book value of equity to market value of equity, where the book value of equity is from the most recently reported fiscal quarter assuming a four-month reporting lag. Mom is the stock return of the previous six months up to the end of Q0. Returns and alphas are in percentage points. The Newey-West t-statistics are computed with a one-quarter lag.

Decile of Pct_Chg	Pct_Chg (%)	Size	B/M	Mom	Return	3-Factor Alpha	4-Factor Alpha
D1(L)	-9.25	5.48	-0.70	4.81	3.59	-0.54 (-1.74)	-0.32 (-1.16)
D2	-2.76	5.54	-0.70	6.15	3.95	-0.14 (-0.50)	0.06 (0.24)
D3	-1.24	5.42	-0.68	7.97	4.11	0.05 (0.17)	0.08 (0.26)
D4	-0.42	5.05	-0.65	9.32	3.98	0.09 (0.27)	-0.11 (-0.37)
D5	0.13	5.01	-0.66	9.80	4.07	0.25 (0.52)	0.14 (0.34)
D6	0.69	5.30	-0.69	11.40	4.34	0.41 (1.37)	0.29 (0.98)
D7	1.41	5.46	-0.73	13.00	4.11	0.08 (0.28)	0.00 (0.01)
D8	2.44	5.57	-0.78	15.24	4.02	-0.09 (-0.36)	-0.11 (-0.47)
D9	4.27	5.60	-0.86	19.22	3.91	-0.12 (-0.56)	-0.21 (-0.89)
D10(H)	11.74	5.51	-1.02	29.99	4.32	0.39 (1.66)	0.10 (0.42)
D10-D1	20.99	0.03	-0.31	25.18	0.73	0.93	**0.42**
t-Stats	(48.25)	(0.75)	(-10.64)	(10.38)	(1.79)	(2.64)	**(1.13)**
P70-P30	10.57	0.08	-0.19	15.17	0.20	0.27	-0.01
t-Stats	(43.80)	1.65	(-9.67)	(11.83)	(0.76)	(1.12)	(-0.05)

Table IV
Value-Weighted Portfolios

Table IV reports the average portfolio-holding-quarter (Q1) portfolio returns (Return), alphas of the Fama-French (1993) 3-factor model and the Carhart (1997) 4-factor model, and t-statistics, of value-weighted decile portfolios formed at the end of each portfolio formation quarter (Q0) based on N_Chg and Pct_Chg respectively. Returns and alphas are in percentage points. The Newey-West t-statistics are computed with a one-quarter lag.

	N_Chg (%)			Pct_Chg (%)		
Decile	Return	3-Factor Alpha	4-Factor Alpha	Return	3-Factor Alpha	4-Factor Alpha
D1(L)	2.40	-1.77	-1.14	3.54	-0.57	-0.32
D2	3.29	-0.87	-0.29	3.95	-0.11	0.13
D3	3.95	-0.39	0.12	4.06	-0.01	0.04
D4	3.13	-0.01	0.31	3.93	0.05	-0.11
D5	2.79	-0.07	0.02	3.95	0.09	0.05
D6	3.82	-0.49	-0.51	4.24	0.27	0.19
D7	4.11	0.01	-0.16	4.05	0.01	-0.01
D8	4.66	0.77	0.42	4.00	-0.08	-0.05
D9	4.73	0.96	0.21	3.86	-0.15	-0.17
D10(H)	5.43	1.98	0.91	4.27	0.36	0.08
D10-D1	3.03	3.74	**2.04**	0.72	0.93	**0.40**
t-Stats	(4.42)	(4.64)	**(4.31)**	(1.77)	(2.69)	**(1.07)**
P70-P30	1.80	2.26	1.00	0.19	0.27	0.00
t-Stats	(3.80)	(3.76)	(3.13)	(0.75)	(1.19)	(0.00)

Table V
Double-Sorted Portfolios (N_Chg)

Table V, Panel A, reports the Carhart (1997) 4-factor alphas of the 25 equal-weighted quintile portfolios sorted first on size (Size) then on N_Chg at the end of each portfolio formation quarter (Q0). Size of a stock is the log of market capitalization (in $millions) calculated based on the stock price and shares outstanding at the end of Q0. Panel B reports the Carhart (1997) 4-factor alphas of the 25 equal-weighted quintile portfolios sorted first on momentum (Mom) then on N_Chg at the end of each portfolio formation quarter (Q0). Mom of a stock is the stock return of the previous six months up to the end of Q0. Alphas are in percentage points. The Newey-West t-statistics are computed with a one-quarter lag.

Panel A: 4-factor Alphas of Equal-Weighted Portfolios sorted first on Size then on N_Chg

		N_Chg Quintile						
		1(L)	2	3	4	5(H)	5(H)-1(L)	t-Stats
Size Quintile	1(L)	-0.70	-0.34	0.66	1.11	0.59	**1.30**	**(3.20)**
	2	-1.00	-0.68	0.08	0.61	0.63	**1.63**	**(3.76)**
	3	-0.61	0.17	-0.09	0.74	0.53	**1.13**	**(2.18)**
	4	-0.92	0.15	-0.14	0.13	0.55	**1.47**	**(2.79)**
	5(H)	-0.22	0.36	-0.13	-0.28	0.06	**0.28**	**(0.47)**

Panel B: 4-factor Alphas of Equal-Weighted Portfolios sorted first on Momentum then on N_Chg

		N_Chg Quintile						
		1(L)	2	3	4	5(H)	5(H)-1(L)	t-Stats
Momentum Quintile	1(L)	-2.00	-0.57	-0.48	0.04	-0.74	**1.26**	**(2.73)**
	2	-0.29	0.39	0.37	0.14	0.61	**0.90**	**(2.81)**
	3	-0.14	-0.01	0.02	0.46	0.53	**0.68**	**(2.19)**
	4	-0.05	-0.50	-0.65	0.23	0.58	**0.63**	**(2.09)**
	5(H)	-0.11	0.07	0.39	0.67	1.68	**1.79**	**(3.17)**

Table VI
Subsample Results (1982-1994)

Table VI reports the average portfolio-holding-quarter (Q1) portfolio returns (Return), alphas of the Fama-French (1993) 3-factor model and the Carhart (1997) 4-factor model, and t-statistics, of equal-weighted decile portfolios formed at the end of each portfolio formation quarter (Q0) based on N_Chg and Pct_Chg respectively from 1982 to 1994. Returns and alphas are in percentage points. The Newey-West t-statistics are computed with a one-quarter lag.

	N_Chg (%)			Pct_Chg (%)		
Decile	Return	3-Factor Alpha	4-Factor Alpha	Return	3-Factor Alpha	4-Factor Alpha
D1(L)	2.36	-1.66	-1.52	3.73	-0.17	-0.07
D2	3.63	-0.40	-0.10	3.88	-0.08	0.05
D3	4.82	0.50	0.55	4.04	-0.15	-0.05
D4	2.57	0.36	0.82	4.28	0.17	0.17
D5	1.97	0.08	0.00	4.15	0.21	0.09
D6	4.15	-0.26	-0.34	4.15	0.13	0.13
D7	4.42	0.15	0.13	4.25	0.24	0.24
D8	5.05	0.86	0.88	4.15	-0.04	-0.13
D9	4.59	0.48	0.29	4.38	0.37	0.39
D10(H)	5.36	1.49	1.03	4.76	0.90	0.71
D10-D1	3.01	3.15	**2.55**	1.02	1.06	**0.78**
t-Stats	(5.54)	(5.20)	**(4.65)**	(2.50)	(2.34)	**(1.65)**
P70-P30	1.50	1.49	1.13	0.54	0.54	0.35
t-Stats	(4.71)	(4.58)	(3.78)	(1.94)	(1.66)	(1.06)

Table VII
Subsample Results (1995-2006)

Table VII reports the average portfolio-holding-quarter (Q1) portfolio returns (Return), alphas of the Fama-French (1993) 3-factor model and the Carhart (1997) 4-factor model, and t-statistics, of equal-weighted decile portfolios formed at the end of each portfolio formation quarter (Q0) based on N_Chg and Pct_Chg respectively from 1995 to 2006. Returns and alphas are in percentage points. The Newey-West t-statistics are computed with a one-quarter lag.

	N_Chg (%)			Pct_Chg (%)		
Decile	Return	3-Factor Alpha	4-Factor Alpha	Return	3-Factor Alpha	4-Factor Alpha
D1(L)	2.79	-1.30	-0.29	3.43	-0.90	-0.48
D2	3.22	-1.01	-0.09	4.02	-0.08	0.39
D3	3.29	-1.16	-0.04	4.18	0.31	0.64
D4	3.61	-0.38	0.03	3.66	0.08	0.08
D5	3.40	-0.35	-0.15	3.98	0.45	0.73
D6	3.63	-0.54	-0.26	4.55	0.85	0.88
D7	4.06	0.10	0.04	3.96	-0.01	0.13
D8	4.37	0.79	0.34	3.88	-0.07	0.20
D9	4.95	1.47	0.38	3.39	-0.62	-0.76
D10(H)	5.53	2.61	1.09	3.84	-0.06	-0.55
D10-D1	2.74	3.91	**1.38**	0.41	0.84	**-0.07**
t-Stats	(2.28)	(3.10)	**(2.09)**	(0.56)	(1.50)	**(-0.13)**
P70-P30	1.90	2.74	0.73	-0.17	-0.03	-0.55
t-Stats	(2.26)	(2.93)	(1.88)	(-0.38)	(-0.08)	(-1.62)

Table VIII
Two-Month Waiting before Portfolio Formation

Table VIII reports the average portfolio-holding-quarter (Q1) portfolio returns (Return), alphas of the Fama-French (1993) 3-factor model and the Carhart (1997) 4-factor model, and t-statistics, of equal-weighted decile portfolios formed two months after the end of each portfolio formation quarter (Q0) based on N_Chg and Pct_Chg respectively. Returns and alphas are in percentage points. The Newey-West t-statistics are computed with a one-quarter lag.

	N_Chg (%)			Pct_Chg (%)		
Decile	Return	3-Factor Alpha	4-Factor Alpha	Return	3-Factor Alpha	4-Factor Alpha
D1(L)	3.02	-1.33	-0.55	3.74	-0.70	0.10
D2	3.71	-0.71	0.12	3.90	-0.51	0.09
D3	3.97	-0.66	0.42	4.22	0.07	0.55
D4	3.33	0.01	0.65	4.30	0.08	0.45
D5	4.06	0.03	0.55	4.09	-0.01	0.40
D6	4.30	-0.36	0.14	4.31	0.14	0.32
D7	3.76	-0.26	-0.15	4.36	0.20	0.44
D8	4.74	0.47	0.45	4.10	-0.19	0.10
D9	4.55	0.63	0.30	4.18	-0.14	-0.04
D10(H)	4.60	0.93	0.42	4.10	-0.03	0.03
D10-D1	1.58	2.27	**0.97**	0.36	0.67	**-0.07**
t-Stats	(3.73)	(5.32)	**(2.25)**	(0.88)	(1.39)	**(-0.17)**
P70-P30	1.06	1.58	0.43	0.17	0.26	-0.22
t-Stats	(3.38)	(4.47)	(1.57)	(0.68)	(0.81)	(-0.77)

Table IX
Long-Run Portfolio Returns

Table IX reports the average portfolio returns of the highest quintile portfolios (5H) and the lowest quintile portfolios (1L), the 5H-1L return differences, and the New-West t-statistics of the 5H-1L return differences in each of the next eight portfolio-holding quarters (from Q1 through Q8) after portfolio formation, with the equal-weighted quintile portfolios formed at the end of each portfolio formation quarter (Q0) based on N_Chg and Pct_Chg respectively. Returns are in percentage points. The Newey-West t-statistics are computed with a one-quarter lag.

	N_Chg (%)				Pct_Chg (%)			
Quarters	5(H)	1(L)	5(H)-1(L)	t-Stats	5(H)	1(L)	5(H)-1(L)	t-Stats
Q1	5.23	3.05	**2.18**	**(4.10)**	4.27	3.82	**0.45**	**(1.44)**
Q2	4.17	3.30	**0.87**	**(2.01)**	3.88	3.43	**0.45**	**(1.50)**
Q3	3.57	3.14	**0.42**	**(0.91)**	3.48	3.39	**0.09**	**(0.31)**
Q4	2.82	3.55	**-0.73**	**(-1.49)**	2.97	3.67	**-0.70**	**(-1.85)**
Q5	2.72	3.40	**-0.68**	**(-1.90)**	3.03	3.62	**-0.59**	**(-2.11)**
Q6	2.96	3.65	**-0.69**	**(-2.33)**	3.21	3.66	**-0.45**	**(-1.75)**
Q7	3.34	3.91	**-0.57**	**(-1.90)**	3.61	3.71	**-0.10**	**(-0.37)**
Q8	3.46	3.90	**-0.44**	**(-1.34)**	3.82	3.83	**-0.01**	**(-0.05)**

Table X
N_Chg and Future Stock Returns

Table X reports the results of various Fama-MacBeth regressions of future stock return on N_Chg with various control variables. In each quarter, I perform cross-sectional regressions of next quarter (Q1)'s return on current-quarter (Q0)'s N_Chg. Control variables include Lag_N_Chg, Lead_N_Chg, Beta, Size, B/M, Mom, E_Chg, Lead_E_Chg, and IV. Lag_N_Chg and Lead_N_Chg are the one-quarter lag and one-quarter lead of N_Chg respectively. Beta is the full-sample beta of the size-beta portfolio which a stock belongs to at the end of Q0 (estimated in the manner of Fama-French (1992)). Size, B/M, and Mom are described earlier, and are measured at the end of Q0. E_Chg is the seasonal change in earnings before extraordinary items (from its one-year-ago value) scaled by average total assets for the fiscal quarter ended in Q0. Lead_E_Chg is the lead-one-quarter value of E_Chg. IV is the idiosyncratic volatility measure estimated in the manner of Ang, Hodrick, Xing, and Zhang (2006). Returns, E_Chg, Lead_E_Chg, and IV are all in percentage points. The coefficient estimates of N_Chg, its one-quarter lead and its one-quarter lag are multiplied by 100. Adj. R^2 is the time-series average of adjusted R-squares. The Newey-West t-statistics are computed with a one-quarter lag.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Intercept	4.00	4.93	4.65	2.83	2.22	2.36	3.78
	(4.28)	(4.13)	(4.02)	(3.20)	(1.90)	(2.00)	(2.75)
Lag_N_Chg (%)				-0.02	0.43	0.42	0.37
				(-0.16)	(1.94)	(1.89)	(1.74)
N_chg (%)	**0.58**	**1.24**	**1.09**	**1.45**	**3.45**	**3.39**	**3.32**
	(2.44)	**(3.47)**	**(3.37)**	**(3.18)**	**(7.18)**	**(7.45)**	**(7.62)**
Lead_N_Chg (%)				22.46	28.43	28.39	28.24
				(11.67)	(12.45)	(12.44)	(12.48)
Beta		-0.00	-0.06		0.01	0.02	0.42
		(-0.00)	(-0.07)		(0.01)	(0.03)	(0.67)
Size		-0.05	-0.03		0.3	0.31	0.16
		(-0.46)	(-0.29)		(2.72)	(2.69)	(1.35)
B/M		0.49	0.79		1.35	1.61	1.44
		(1.37)	(2.42)		(4.97)	(6.04)	(5.95)
Mom			0.02		-0.01	-0.03	-0.03
			(4.09)		(-2.45)	(-5.72)	(-5.62)
E_Chg (%)						0.38	0.37
						(11.89)	(11.93)
Lead_E_Chg (%)						0.66	0.66
						(11.93)	(11.80)
IV							-0.53
							(-2.99)
Adj. R^2	0.09%	4.43%	5.02%	6.80%	12.31%	14.80%	15.52%

Table XI
Pct_Chg and Future Stock Returns

Table XI reports the results of various Fama-MacBeth regressions of future stock return on Pct_Chg with various control variables. In each quarter, I perform cross-sectional regressions of next quarter (Q1)'s return on current-quarter (Q0)'s Pct_Chg. Control variables include Lag_Pct_Chg, Lead_Pct_Chg, Beta, Size, B/M, Mom, E_Chg, Lead_E_Chg, and IV. Lag_Pct_Chg and Lead_Pct_Chg are the one-quarter lag and one-quarter lead of Pct_Chg respectively. Beta is the full-sample beta of the size-beta portfolio which a stock belongs to at the end of Q0 (estimated in the manner of Fama-French (1992)). Size, B/M, and Mom are described earlier, and are measured at the end of Q0. E_Chg is the seasonal change in earnings before extraordinary items (from its one-year-ago value) scaled by average total assets for the fiscal quarter ended in Q0. Lead_E_Chg is the lead-one-quarter value of E_Chg. IV is the idiosyncratic volatility measure estimated in the manner of Ang, Hodrick, Xing, and Zhang (2006). Returns, E_Chg, Lead_E_Chg, and IV are all in percentage points. Adj. R^2 is the time-series average of adjusted R-squares. The Newey-West t-statistics are computed with a one-quarter lag.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Intercept	4.03	5.08	4.78	3.64	4.62	4.72	5.95
	(4.33)	(4.24)	(4.13)	(4.00)	(3.90)	(3.95)	(4.23)
Lag_Pct_Chg (%)				0.03	0.06	0.05	0.04
				(2.19)	(4.77)	(4.02)	(3.65)
Pct_Chg (%)	**0.03**	**0.01**	**-0.02**	**0.11**	**0.10**	**0.09**	**0.09**
	(1.67)	**(0.68)**	**(-1.68)**	**(5.20)**	**(6.29)**	**(6.24)**	**(5.66)**
Lead_Pct_Chg (%)				0.53	0.53	0.55	0.54
				(11.42)	(10.86)	(11.62)	(11.43)
Beta		-0.01	-0.07		-0.25	-0.21	0.15
		(-0.01)	(-0.08)		(-0.29)	(-0.25)	(0.22)
Size		-0.07	-0.05		-0.01	0.00	-0.13
		(-0.63)	(-0.40)		(-0.08)	(0.03)	(-1.12)
B/M		0.41	0.75		0.86	1.15	1.00
		(1.13)	(2.29)		(2.78)	(3.79)	(3.67)
Mom			0.03		0.01	-0.01	-0.01
			(4.54)		(2.22)	(-1.29)	(-1.04)
E_Chg (%)						0.43	0.42
						(12.80)	(12.81)
Lead_E_Chg (%)						0.69	0.69
						(11.92)	(11.79)
IV							-0.48
							(-2.57)
Adj. R^2	0.10%	4.38%	4.99%	2.87%	7.54%	10.25%	10.99%

Table XII
Long-Run Portfolio Seasonal Earnings Growth

Table XII reports the average seasonal earnings growth rates of the highest quintiles (5H) and the lowest quintiles (1L), the 5H-1L seasonal earnings growth differences, and the New-West t-statistics of the 5H-1L differences for each of the four quarters before portfolio formation (i.e., Q_3, Q_2, Q_1 and Q0) and each of the eight quarters after portfolio formation (i.e., Q1, Q2, Q3, Q4, Q5, Q6, Q7 and Q8), with the equal-weighted quintile portfolios formed at the end of each Q0 based on N_Chg and Pct_Chg respectively. Seasonal earnings growth rate of a firm in a quarter is measured as the firm's seasonal change in earnings before extraordinary items (from the one-year-ago quarterly value) for the quarter scaled by its average total asset. The measure is industry-demedianed (i.e., subtracted by the corresponding two-digit-SIC industry median), and is reflected in percentage points. The Newey-West t-statistics are computed with an eight-quarter lag.

	N_Chg (%)				Pct_Chg (%)			
Quarters	5(H)	1(L)	5(H)-1(L)	t-Stats	5(H)	1(L)	5(H)-1(L)	t-Stats
Q_3	0.17	-0.05	**0.22**	**(5.57)**	0.07	0.03	**0.04**	**(1.00)**
Q_2	0.21	-0.16	**0.37**	**(8.80)**	0.11	-0.04	**0.15**	**(4.76)**
Q_1	0.30	-0.37	**0.66**	**(12.96)**	0.14	-0.16	**0.30**	**(8.25)**
Q0	0.20	-0.44	**0.64**	**(13.78)**	0.09	-0.24	**0.33**	**(7.33)**
Q1	0.09	-0.49	**0.58**	**(11.24)**	0.04	-0.32	**0.36**	**(9.08)**
Q2	-0.04	-0.46	**0.41**	**(10.71)**	-0.06	-0.35	**0.29**	**(7.01)**
Q3	-0.20	-0.29	**0.09**	**(2.77)**	-0.17	-0.27	**0.10**	**(4.68)**
Q4	-0.25	-0.21	**-0.04**	**(-0.76)**	-0.18	-0.19	**0.01**	**(0.74)**
Q5	-0.25	-0.08	**-0.17**	**(-3.06)**	-0.17	-0.13	**-0.05**	**(-1.17)**
Q6	-0.18	-0.04	**-0.14**	**(-1.80)**	-0.13	-0.07	**-0.05**	**(-1.72)**
Q7	-0.18	0.01	**-0.19**	**(-4.18)**	-0.10	-0.02	**-0.08**	**(-1.98)**
Q8	-0.09	0.03	**-0.11**	**(-2.05)**	-0.05	-0.02	**-0.03**	**(-0.87)**

Table XIII
Long-Run Portfolio Seasonal Net Operating Cash Flow Growth

Table XIII reports the average seasonal net operating cash flow (OCF) growth rates of the highest quintiles (5H) and the lowest quintiles (1L), the 5H-1L seasonal net OCF growth differences, and the New-West t-statistics of the 5H-1L differences for each of the four quarters before portfolio formation (i.e., Q_3, Q_2, Q_1 and Q0) and each of the eight quarters after portfolio formation (i.e., Q1, Q2, Q3, Q4, Q5, Q6, Q7 and Q8), with the equal-weighted quintile portfolios formed at the end of each Q0 based on N_Chg and Pct_Chg respectively. Seasonal net OCF growth rate of a firm in a quarter is measured as the firm's seasonal change in net OCF (from the one-year-ago quarterly value) for the quarter scaled by its average total asset. The measure is industry-demedianed (i.e., subtracted by the corresponding two-digit-SIC industry median), and is reflected in percentage points. The Newey-West t-statistics are computed with an eight-quarter lag.

	N_Chg (%)				Pct_Chg (%)			
Quarters	5(H)	1(L)	5(H)-1(L)	t-Stats	5(H)	1(L)	5(H)-1(L)	t-Stats
Q_3	0.13	-0.14	**0.27**	**(2.66)**	0.10	-0.01	**0.12**	**(2.17)**
Q_2	0.32	-0.38	**0.71**	**(6.96)**	0.21	-0.10	**0.31**	**(5.66)**
Q_1	0.32	-0.50	**0.82**	**(4.99)**	0.18	-0.18	**0.36**	**(3.49)**
Q0	0.30	-0.68	**0.98**	**(5.87)**	0.17	-0.19	**0.36**	**(3.73)**
Q1	0.05	-0.65	**0.70**	**(3.70)**	0.14	-0.29	**0.43**	**(5.43)**
Q2	-0.15	-0.54	**0.39**	**(2.49)**	0.06	-0.29	**0.35**	**(4.90)**
Q3	-0.19	-0.24	**0.05**	**(0.47)**	0.03	-0.06	**0.09**	**(0.90)**
Q4	-0.06	-0.03	**-0.03**	**(-0.49)**	0.05	0.01	**0.04**	**(0.57)**
Q5	0.05	0.03	**0.01**	**(0.13)**	0.09	0.08	**0.01**	**(0.16)**
Q6	0.13	0.06	**0.07**	**(0.58)**	0.12	0.11	**0.01**	**(0.13)**
Q7	0.11	0.06	**0.05**	**(0.36)**	0.17	0.09	**0.07**	**(0.91)**
Q8	0.15	0.09	**0.06**	**(0.33)**	0.20	0.11	**0.08**	**(1.14)**

Table XIV
Long-Run Portfolio Seasonal Sales Growth

Table XIV reports the average seasonal sales growth rates of the highest quintiles (5H) and the lowest quintiles (1L), the 5H-1L seasonal sales growth differences, and the New-West t-statistics of the 5H-1L differences for each of the four quarters before portfolio formation (i.e., Q_3, Q_2, Q_1 and Q0) and each of the eight quarters after portfolio formation (i.e., Q1, Q2, Q3, Q4, Q5, Q6, Q7 and Q8), with the equal-weighted quintile portfolios formed at the end of each Q0 based on N_Chg and Pct_Chg respectively. Seasonal sales growth rate of a firm in a quarter is measured as the firm's net sales of the quarter minus its net sales of the corresponding one-year-ago quarter then divided by its net sales of the corresponding one-year-ago quarter. The measure is industry-demedianed (i.e., subtracted by the corresponding two-digit-SIC industry median), and is reflected in percentage points. The Newey-West t-statistics are computed with an eight-quarter lag.

	N_Chg (%)				Pct_Chg (%)			
Quarters	5(H)	1(L)	5(H)-1(L)	t-Stats	5(H)	1(L)	5(H)-1(L)	t-Stats
Q_3	15.74	10.19	**5.55**	**(5.03)**	12.27	11.06	**1.21**	**(1.91)**
Q_2	16.96	9.41	**7.56**	**(7.27)**	13.36	10.78	**2.57**	**(4.02)**
Q_1	19.15	7.92	**11.23**	**(8.05)**	15.02	9.28	**5.74**	**(6.26)**
Q0	20.01	6.55	**13.46**	**(7.53)**	15.32	8.53	**6.79**	**(6.42)**
Q1	19.68	5.56	**14.12**	**(7.70)**	15.03	7.32	**7.71**	**(7.47)**
Q2	18.07	5.16	**12.91**	**(6.99)**	13.88	6.42	**7.47**	**(6.36)**
Q3	15.34	4.93	**10.42**	**(6.91)**	11.95	5.76	**6.19**	**(6.00)**
Q4	12.89	4.53	**8.36**	**(7.03)**	10.34	5.45	**4.89**	**(6.09)**
Q5	11.14	4.73	**6.42**	**(7.34)**	9.16	5.09	**4.07**	**(5.72)**
Q6	9.85	4.38	**5.47**	**(9.06)**	8.50	4.65	**3.85**	**(7.57)**
Q7	8.83	4.44	**4.39**	**(7.08)**	7.78	4.58	**3.20**	**(8.02)**
Q8	8.07	4.48	**3.59**	**(7.14)**	7.28	4.19	**3.09**	**(7.37)**

Table XV
Institutional Ownership and Tobin's Q

Table XV reports the results of Fama-MacBeth regressions of Tobin's Q on N_Chg and Pct_Chg respectively, with various control variables. In each quarter, I perform cross-sectional regressions of Tobin's Q on current-quarter N_Chg and Pct_Chg respectively. Control variables include Log(assets), Mom, Lag_Q, and industry dummies. Tobin's Q is calculated as book value of assets minus book value of common equity minus deferred taxes plus market value of common equity and then divided by book value of assets, and is measured at the end of current quarter (Q0) with the relevant accounting information being from the most recently reported fiscal quarter (assuming a four-month reporting lag). Lag_Q is the one-quarter lag of Tobin's Q. Log(assets) is the log of book value of assets. Mom is the stock return of the previous six months up to the end of Q0 and is in percentage points. The coefficient estimates of industry dummies are not reported for brevity. The coefficient estimate of N_Chg is multiplied by 100. Adj. R^2 is the time-series average of adjusted R-squares. The Newey-West t-statistics are computed with a four-quarter lag.

	Model 1	Model 2
Intercept	0.37	0.39
	(6.94)	(6.96)
N_Chg (%)	**0.22**	
	(5.34)	
Pct_Chg (%)		**0.01**
		(4.84)
Log(assets)	-0.03	-0.03
	(-7.35)	(-7.33)
Mom	0.01	0.01
	(11.16)	(11.07)
Lag_Q	0.82	0.82
	(32.60)	(32.61)
Industry dummies	Yes	Yes
Adj. R^2	83.54%	83.49%

Table XVI
Institutional Ownership, Sentiment Beta and Future Stock Return

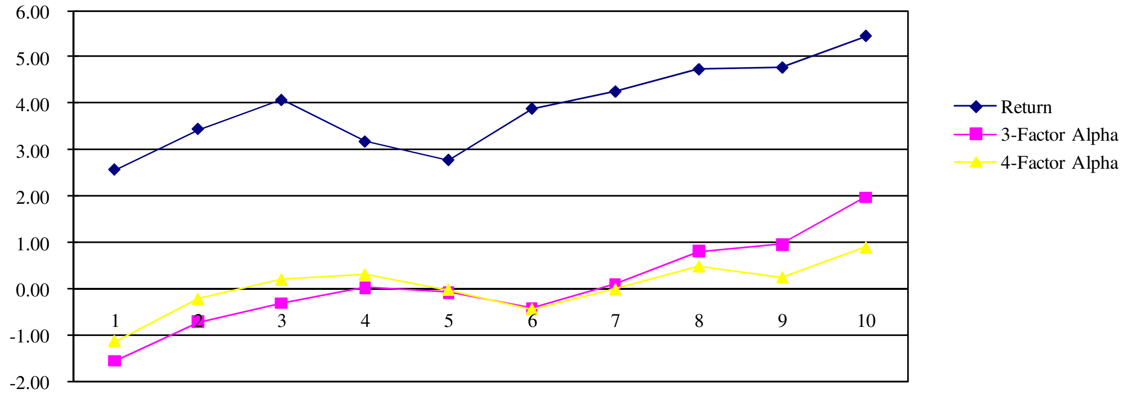
Table XVI reports the results of various Fama-MacBeth regressions of future stock return on N-Chg (or Pct_Chg), the interaction term between sentiment beta and N_Chg (or that between sentiment beta and Pct_Chg), and control variables. Sentiment beta is measured in the following way: at the end of December in each year, I perform time-series regression of monthly return on Baker and Wurgler (2007)'s index of sentiment changes (macro-effect removed) and CRSP value-weighted index return for each stock over the past 60 months (24 months at least) to obtain its pre-ranking sentiment beta (i.e., the regression coefficient of the sentiment change index); I then independently sort stocks into size and pre-ranking sentiment beta deciles (based on NYSE decile breakpoints) to form 100 size-sentiment beta portfolios and hold them over the next 12 months; for each of the 100 portfolio, I then perform time-series regression of the monthly equal-weighted portfolio return on BW's sentiment change index (macro-effect removed) and CRSP value-weighted index return over the entire sample period to estimate its full-sample sentiment beta. The variable, sentiment beta, used in the FM regressions is the full-sample sentiment beta of the size-sentiment beta portfolio which a stock belongs to at the beginning of the year which Q0 belongs to. In each regression model, Beta, Size, B/M and Mom are also included as control variables, but they are omitted from the table for brevity. The Newey-West t-statistics are computed with a one-quarter lag.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	4.50	2.22	3.27	4.59	4.44	5.48
	(3.95)	(1.88)	(2.37)	(4.05)	(3.81)	(3.97)
Lag_N_Chg (%)		0.92	0.88			
		(2.86)	(2.68)			
N_Chg (%)	1.05	4.34	4.10			
	(3.15)	(8.91)	(9.34)			
Sentiment Beta*N_Chg (%)	**2.54**	**2.39**	**2.19**			
	(2.82)	**(3.01)**	**(2.57)**			
Lead_N_Chg (%)		31.58	31.48			
		(12.96)	(13.14)			
Lag_Pct_Chg (%)					0.06	0.04
					(4.66)	(3.63)
Pct_Chg (%)				-0.03	0.09	0.08
				(-2.79)	(5.99)	(5.31)
Sentiment Beta*Pct_Chg (%)				**11.50**	**8.92**	**10.60**
				(1.90)	**(1.54)**	**(1.79)**
Lead_Pct_Chg (%)					0.48	0.50
					(10.34)	(10.87)
Sentiment Beta	-5.74	-27.47	-18.23	-1.67	-4.11	3.46
	(-0.24)	(-1.29)	(-0.99)	(-0.07)	(-0.19)	(0.18)
E_Chg (%)			0.35			0.41
			(10.09)			(11.26)
Lead_E_Chg (%)			0.71			0.75
			(12.49)			(12.73)
IV			-0.42			-0.42
			(-2.23)			(-2.20)
Adj. R^2	5.34%	12.95%	16.04%	5.29%	7.71%	11.04%

Figure 1
Returns and Alphas of Decile Portfolios Sorted by Institutional Ownership Variables

Figure 1 plots the average portfolio returns, 3-facotor alphas and 4-factor alphas of equal-weighted decile portfolios sorted by N_Chg and Pct_Chg respectively.

Panel A: Returns and Alphas of Decile Portfolios Sorted by N_Chg



Panel B: Returns and Alphas of Decile Portfolios Sorted by Pct_Chg

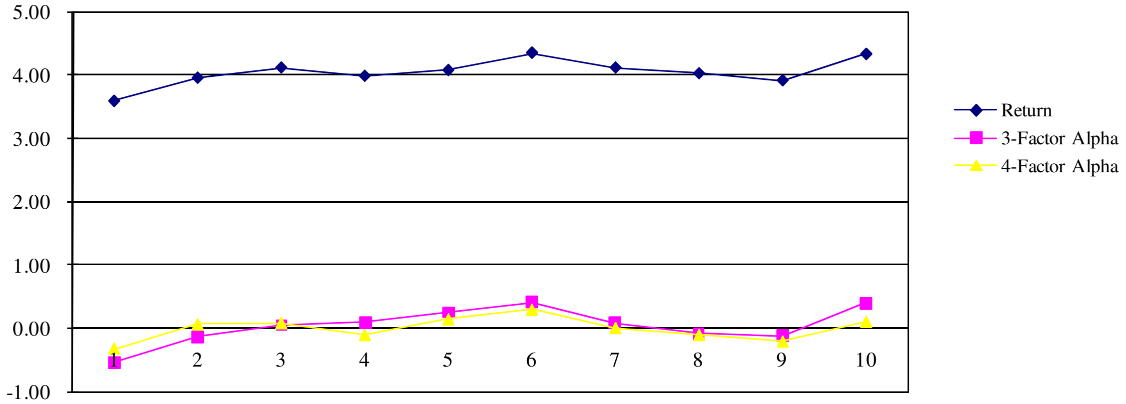


Figure 2
Time-Series of Returns of Zero-Investment D10-D1 Strategies

Figure 2 plots the two time-series of the annual returns of the two zero-investment strategies that long D10 and short D1, with the equal-weighted decile portfolios formed by sorting on past N_Chg and Pct_Chg respectively.

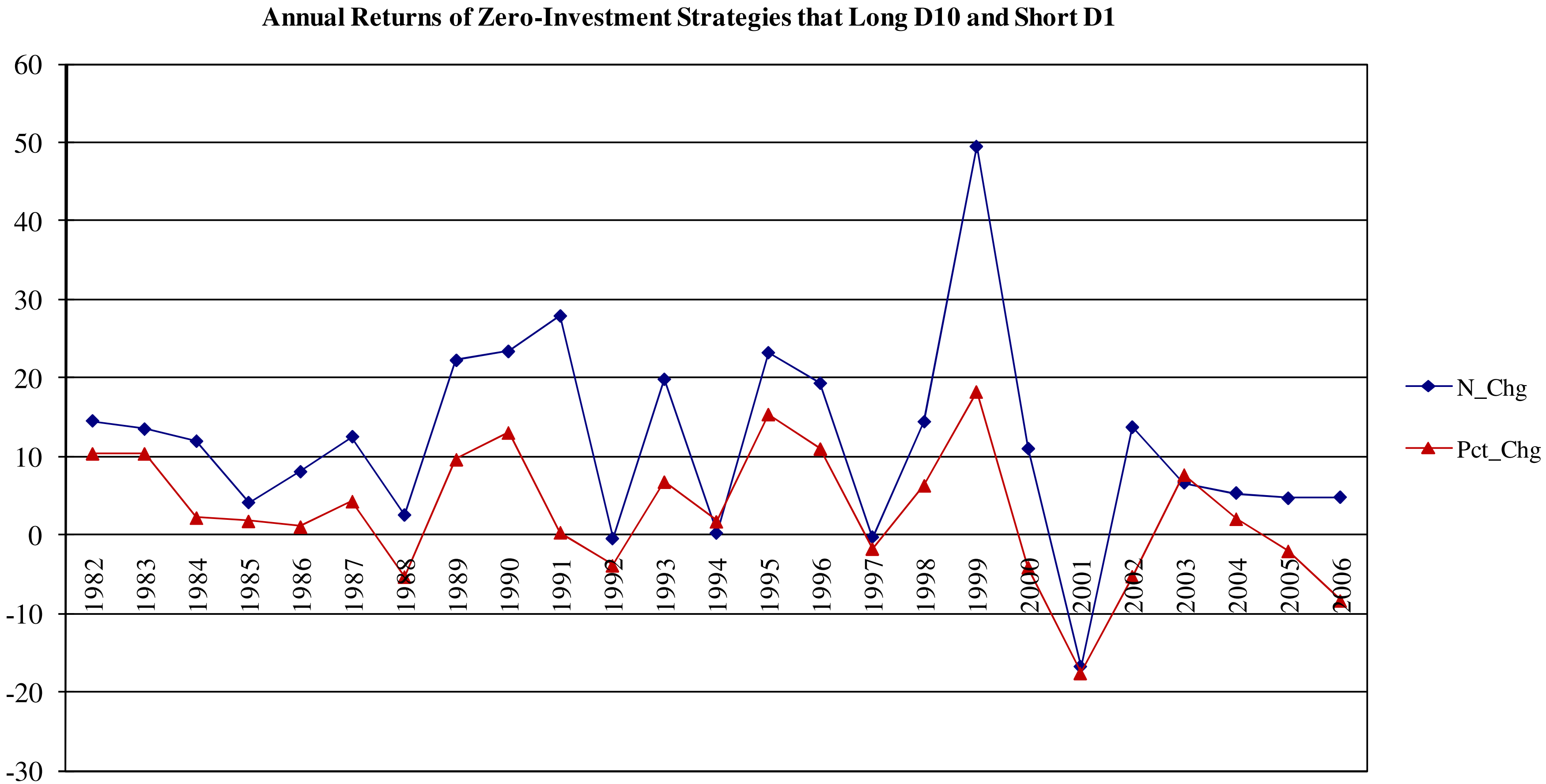


Figure 3
Long-Run Portfolio Return Differences

Figure 3 plots the average portfolio return difference between the highest quintile portfolio (5H) and the lowest quintile portfolio (1L) in each of the next eight portfolio-holding quarters after portfolio formation (from Q1 through Q8), with the equal-weighted quintile portfolios formed at the end of each portfolio formation quarter (Q0) based on N_Chg and Pct_Chg respectively.

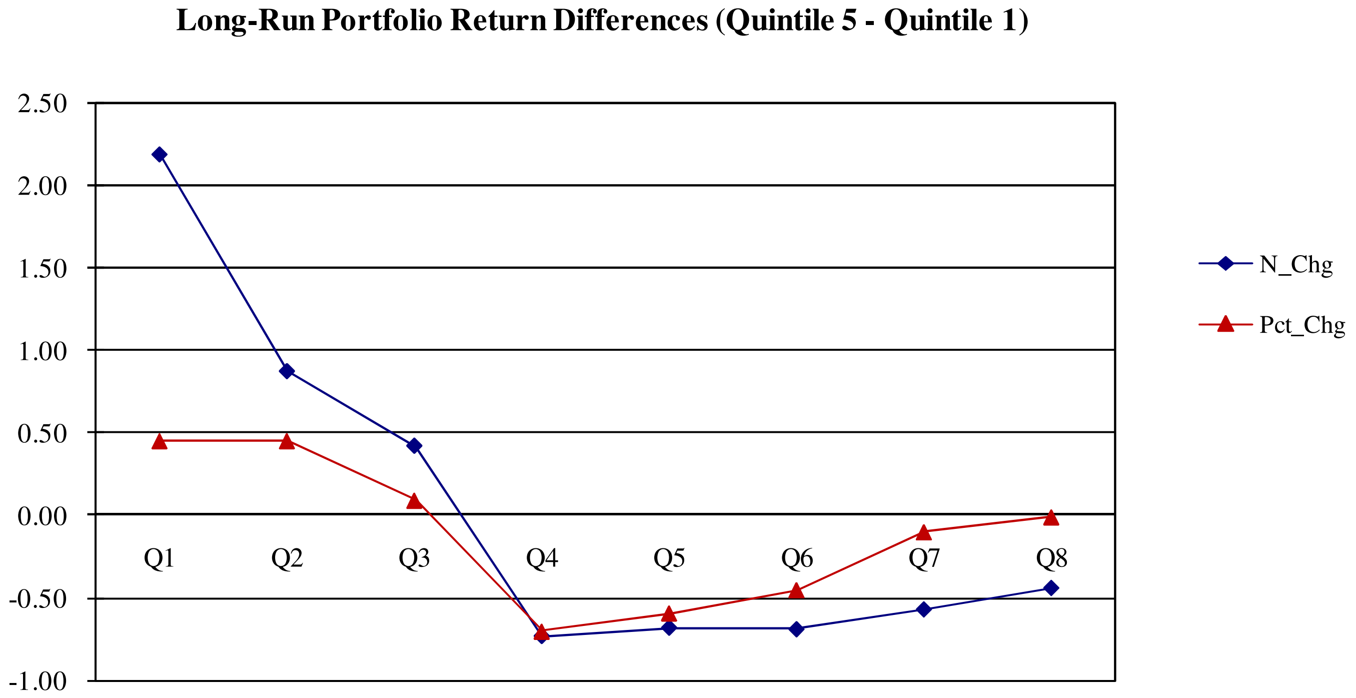


Figure 4
Long-Run Seasonal Earnings Growth Differences

Figure 4 plots the average seasonal earnings growth rate differences between the highest quintiles (5H) and the lowest quintiles (1L) in each of the prior four quarters before portfolio formation (i.e., Q_3, Q_2, Q_1, Q0) and each of the next eight portfolio-holding quarters after portfolio formation (i.e., Q1, Q2, Q3, Q4, Q5, Q6, Q7 and Q8), with the equal-weighted quintile portfolios formed at the end of each Q0 based on N_Chg and Pct_Chg respectively.

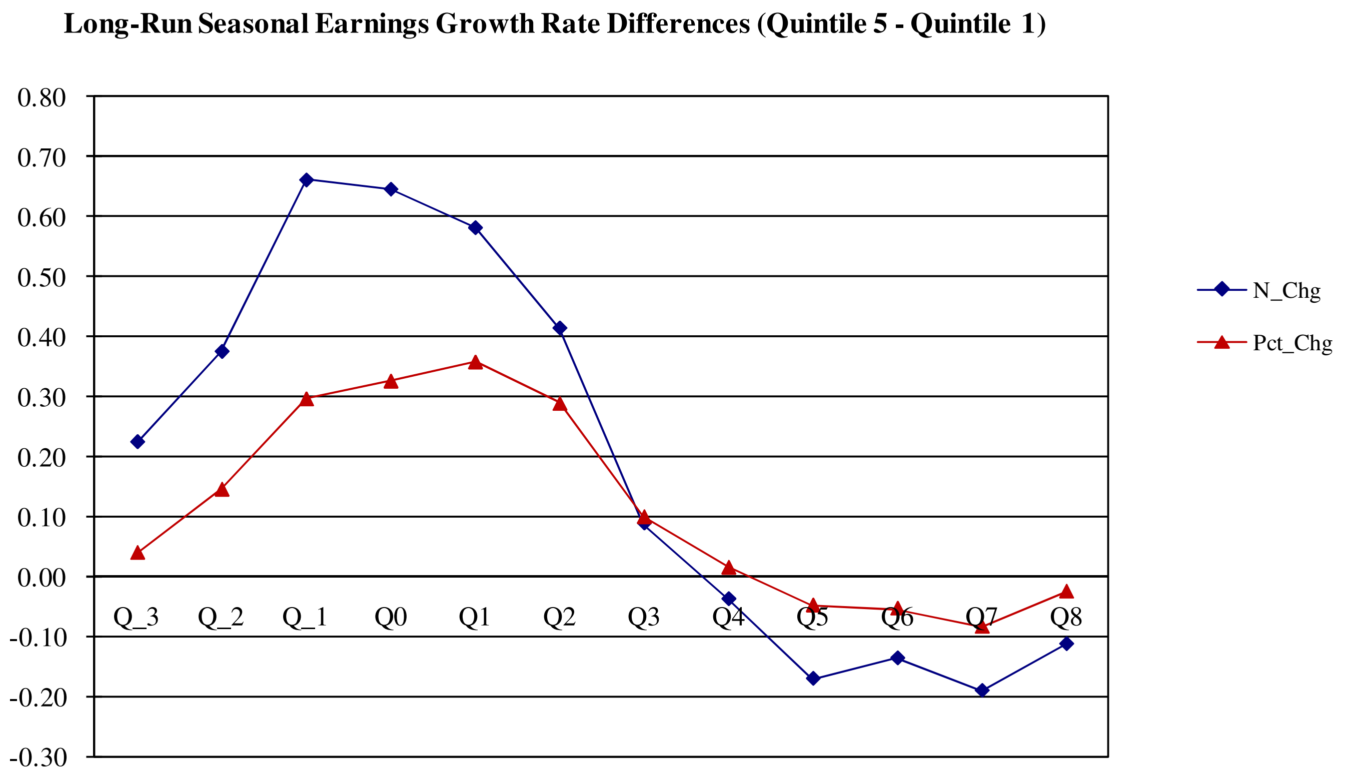


Figure 5
Long-Run Seasonal Net Operating Cash Flow Growth Differences

Figure 5 plots the average seasonal net operating cash flow growth rate differences between the highest quintiles (5H) and the lowest quintiles (1L) in each of the prior four quarters before portfolio formation (i.e., Q_3, Q_2, Q_1, Q0) and each of the next eight portfolio-holding quarters after portfolio formation (i.e., Q1, Q2, Q3, Q4, Q5, Q6, Q7 and Q8), with the equal-weighted quintile portfolios formed at the end of each Q0 based on N_Chg and Pct_Chg respectively.

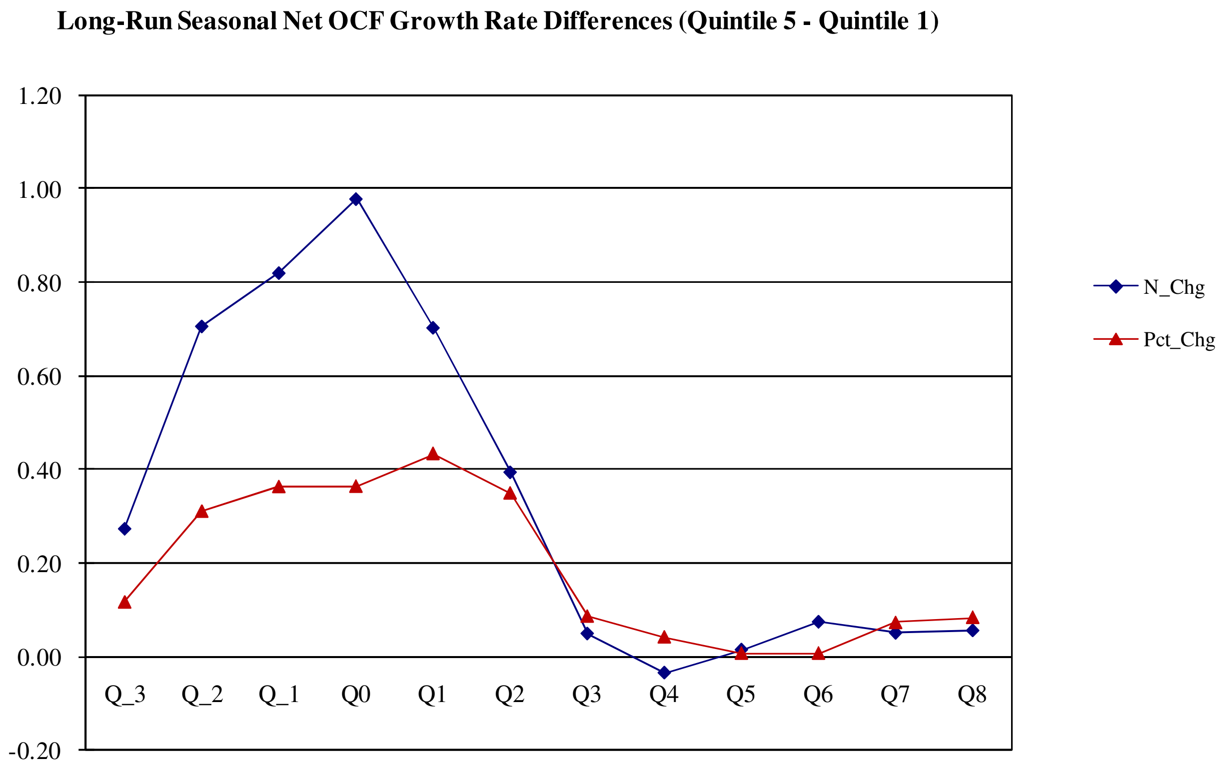


Figure 6
Long-Run Seasonal Sales Growth Differences

Figure 6 plots the average seasonal sales growth rate differences between the highest quintiles (5H) and the lowest quintiles (1L) in each of the prior four quarters before portfolio formation (i.e., Q_3, Q_2, Q_1, Q0) and each of the next eight portfolio-holding quarters after portfolio formation (i.e., Q1, Q2, Q3, Q4, Q5, Q6, Q7 and Q8), with the equal-weighted quintile portfolios formed at the end of each Q0 based on N_Chg and Pct_Chg respectively.