# Continuing Overreaction and Stock Return Predictability

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**Abstract**

Prior studies argue that overconfidence-driven market overreaction leads to return predictability and high trading volume. Motivated by these studies, we propose a measure of continuing overreaction based on weighted signed volumes and examine whether it predicts future returns. We find that the strategies of buying stocks with upward continuing overreaction and selling stocks with downward continuing overreaction generate significant positive returns. Furthermore, the momentum effect disappears after controlling for the effect of continuing overreaction. An alternative measure of continuing overreaction constructed from volatility gives similar results. Our results provide direct support for the behavioral model of return predictability based on investor overconfidence.

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# 1. Introduction

Recent studies in behavioral finance argue that anomalous behavior in security markets can be better understood when we consider deviations from rationality such as judgment biases and nonstandard preferences. In particular, a number of studies show that overconfidence can explain a wide range of phenomena in stock markets and corporate decisions. Based on the large volume of evidence in psychology literature documenting overconfidence in human judgment,[1] it is not surprising that overconfidence performs quite well in explaining stock returns and the behavior of market participants.

Daniel, Hirshleifer, and Subrahmanyam (1998, DHS hereafter) show that investor overconfidence and biased self-attribution can explain both underreactions and overreactions in the stock market. In their model, investors initially overreact to their private information as they are overconfident about their ability; subsequent arrivals of public signals on average increase their overconfidence due to biased self-attribution and trigger further overreaction to the private information. Such continuing overreaction to private information causes momentum in the short-run. In other words, past returns predict future returns because high (low) past returns indicate investors are becoming more overconfident in their positive (negative) private information, which leads to further overreaction to their positive (negative) private information.

If continuing overreaction causes momentum as described by DHS, a more direct measure of continuing overreaction than past returns can be a better predictor of future returns. In this paper we present evidence that continuing overreaction leads to return predictability by introducing a new measure that captures continuing overreaction and directly relating it to future stock returns. As we show in Appendix A, the DHS model implies that measures of continuing overreaction predict future returns and that they have a stronger predictive power than past returns on future returns. Our measure of continuing overreaction is constructed

[1] Debondt and Thaler (1995) state in their survey that "perhaps the most robust finding in the psychology of judgment is that people are overconfident."

from monthly trading volume and the sign of contemporaneous stock returns. Benos (1998) and Odean (1998) show theoretically that overconfidence increases trading volume. The relation between the degree of overconfidence and trading volume has been empirically examined in a number of studies (e.g., Barber and Odean, 2001; Glaser and Weber, 2009; Grinblatt and Keloharju, 2009; Statman, Thorley, and Vorkink, 2006). Therefore, it is reasonable to use trading volume as a proxy of the degree of investor overconfidence and overreaction.

The level of investor overconfidence, however, does not predict future returns by itself. To predict future returns, we first need to identify the *direction* of investor overreaction. Investors' continuing overreaction accompanied by an increasing stock price indicates that they are becoming more overconfident about their positive private signal; therefore, it predicts a higher future stock price. On the other hand, investors' continuing overreaction accompanied by a decreasing stock price indicates their increasing overconfidence about their negative private signal and predicts a lower future stock price. By multiplying the trading volume by the sign of the contemporaneous return, we construct signed volume which incorporates the direction of investor overreaction. Secondly, we need a measure that captures the *time-trend* in overconfidence rather than the level of overconfidence since continuing overreaction is characterized by an upward trend in overconfidence. DHS show that overconfidence alone does not predict momentum, and that momentum arises when investors become increasingly more confident about their private information due to biased self-attribution. Therefore, we assign a larger weight on the signed volume of a more recent month and take the weighted sum of signed volumes. Further, we normalize the weighted sum of signed volumes by the average volume over the same period so that we are capturing the *trend* rather than *level* of overconfidence.

Thus, we introduce a measure of continuing overreaction (CO) that is based on the summation of weighted monthly signed volumes during the past 12 months and examine whether the measure predicts future returns. When we sort stocks by the CO measure and group them into ten portfolios, we find that the strategy of buying stocks with the strongest degree of continuing overreaction on the positive side (decile 10) and selling stocks with the strongest degree of continuing overreaction on the negative side (decile 1) generates significant positive returns for 3- to 12-month holding periods.

Since our continuing overreaction strategies are motivated by the behavioral explanation of momentum as in DHS, we carefully compare our strategies with price momentum strategies (Jegadeesh and Titman, 1993, 2001). Although we use the sign not the magnitude of the return when we construct the CO measure, stocks in the winner (loser) portfolio are more likely to have high (low) values of CO. Hence, we investigate whether the profitability of our strategy is explained by price momentum using momentum-adjusted returns, double sorts based on momentum and CO, and cross-sectional regressions. We find that not only are the returns of our strategies based on CO robust to controlling for momentum, but the returns of the momentum portfolios, except for the loser portfolio, become insignificant after adjusting for CO. In a cross-sectional regression with CO and past returns as independent variables, the coefficient of past returns is not significant, whereas the coefficient of CO is highly significant at the 1% level. CO remains as a significant predictor of future returns when we add other determinants of the cross-section of stock returns such as beta, size, book-to-market, one-month return reversal, liquidity, idiosyncratic volatility, turnover, and unrealized capital gains (Grinblatt and Han, 2005). These results from portfolio and cross-sectional regression analyses indicate that our strategies based on CO are distinct from the momentum strategies, and the profits from our strategies subsume momentum profits as well.

We also examine whether the continuing overreaction effect is explained by the effect of return consistency (Grinblatt and Moskowitz, 2004) or information discreteness (Da, Gurun, and Warachka, 2012) since stocks that have experienced a series of returns in the same direction tend to have large absolute values of CO. Our empirical results show that the continuing overreaction effect is robust to the effects of return consistency and information discreteness.

For robustness, we repeat the analyses using an alternative measure of continuing overreaction. Daniel, Hirshleifer, and Subrahmanyam (1998) and Odean (1998) show a positive relation between the level of investor overconfidence and volatility, therefore we construct an alternative measure of continuing overreaction based on volatility instead of trading volume. The results are qualitatively the same using the alternative measure of continuing overreaction.

Our results provide direct support for the behavioral explanation of momentum by DHS. Our CO measure is designed to capture the underlying mechanism of return predictability in their model and we find that it is a better predictor of future returns than past returns, subsuming the momentum effect. This implies that continuing overreaction leads to return predictability and explains the momentum effect.

Several empirical studies also provide evidence supporting DHS. Chui, Titman, and Wei (2010) document that an individualism index, which is related to overconfidence and self-attribution, is positively related to the magnitude of momentum profits around the world. Da, Engelberg, and Gao (2010) show that momentum is stronger among stocks searched more frequently in Google, and argue that their result supports the overconfidence model of momentum. Hwang (2010) finds that momentum profits increase in the average correlation of analysts' forecast errors, and argues that these results are consistent with DHS. Cooper, Gutierrez Jr, and Hameed (2004) find that momentum strategies are profitable only following periods of market gains, and Hou, Peng, and Xiong (2008) show that momentum profits are higher among high volume stocks and in up markets. Since investors are more likely to be overconfident after investment gains (e.g., Gervais and Odean, 2001), these results support the overreaction model of momentum. These studies focus on the relation between their empirical variable and the strength of the momentum effect. What separates our paper from theirs is that we directly relate a measure of continuing overreaction to future stock returns.

Our study is also related to the literature on the relation between trading volume and the autocorrelation of stock returns. A number of studies have examined the relation between trading volume and daily or weekly price movements (e.g., Campbell, Grossman, and Wang, 1993; Conrad, Hameed, and Niden, 1994; Cooper, 1999). In longer horizons, Lee and Swaminathan (2000) show that high volume winners and low volume losers experience faster reversals, while low volume winners and high volume losers show return continuations. These studies examine how trading volume affects the relation between past and future returns. In contrast, we examine the return predictability of a time-trend in signed trading volume itself, not how trading volume affects the relation between past and future returns. In addition, our CO measure is normalized by the average trading volume during the formation period, thus it is unlikely to capture the effects of the level of trading volume (e.g., Lee and Swaminathan, 2000).[2]

# 2. Methodology

## *2.1. Continuing Overreaction Measure*

DHS develop a theory based on investor overconfidence and biased self-attribution, and show that investors' continuing overreaction leads to short-term momentum and long-term reversals. In Appendix A, we show using their model that measures of investors' continuing overreaction predict future returns, and that such measures of continuing overreaction have stronger predictive powers of future returns compared to past returns.

Motivated by DHS, we construct our empirical measure of continuing overreaction in the following way. First, we use monthly trading volume as a proxy of the degree of investor overreaction (e.g., Benos, 1998; Odean, 1998).[3] The simulation results in Appendix A show that a measure of continuing overreaction based on trading volume is a good proxy of that directly based on the level of overconfidence. To identify the direction of investor overreaction, we use the sign of contemporaneous returns and construct monthly signed volumes. Next,

[2] Panel B of Table 1 shows no discernible pattern in average turnover across CO deciles. The cross-sectional regression analyses control for the level of trading volume.

[3] We also replicated our tests using weekly signed volumes and found similar results.

we assign increasing weights to signed volumes of more recent months to identify whether or not investor overreaction increases or decreases over time. Thus, we assume that a series of investor reactions in the same direction with an increasing intensity indicates a higher level of continuing overreaction.

The *signed volume* for stock $i$ in month $t$, $SV_{i,t}$, is defined as

$$SV_{i,t} = \begin{cases} vol_{i,t} & \text{if } r_{i,t} > 0 \\ 0 & \text{if } r_{i,t} = 0 \\ -vol_{i,t} & \text{if } r_{i,t} < 0 \end{cases} \tag{1}$$

where $vol$ is the trading volume and $r$ is the stock return.

After assigning higher weights to signed volumes in more recent months, we sum them and normalize the sum by the average of raw trading volumes over the same period. This is for capturing the *trend* rather than *level* of overconfidence and allows comparison across firms. It also ensures that we are not merely capturing the effect of trading volume, which has already been extensively studied (e.g., Lee and Swaminathan, 2000). Therefore, our measure of continuing overreaction, denoted by CO, is defined as

$$\mathrm{CO}_{i,t} = \frac{sum(w_J \cdot SV_{i,t-J}, \cdots, w_1 \cdot SV_{i,t-1})}{mean(vol_{i,t-J}, \cdots, vol_{i,t-1})}, \tag{2}$$

where $SV_{i,t}$ is the signed volume for stock $i$ in month $t$, $J$ is the length of the formation period, and $w_j$ is a weight that takes a value of $J - j + 1$ in month $t - j$ (i.e., $w_J = 1$, $w_{J-1} = 2$, and $w_1 = J$).[4] We use a one-year formation period throughout the paper ($J = 12$).[5] We use dollar volume as a measure of trading volume, but for robustness we also use share volume that is adjusted for changes in the number of shares outstanding and find similar results (unreported). As the CO measure is normalized by the average trading volume over the same period, both share volume and turnover produce the same values.

[4]For sensitivity analysis, we have employed a series of alternative linear and non-linear weighting schemes that assign higher weights to more recent months and found similar results. These results are available upon request.

[5]The 9- and 15-month formation periods ($J = 9, 15$) produce qualitatively similar results.

## 2.2. Sample

Our sample consists of firms traded on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ from the Center for Research in Security Prices (CRSP) for the period from January 1965 to December 2009. We exclude all primes and scores, closed-end funds, REITs, ADRs, and foreign companies. NASDAQ firms are usually eliminated in studies using trading volume since the trading volume of NASDAQ stocks cannot be compared with those of NYSE and AMEX stocks due to the double counting of trades in multiple dealer markets (see Gould and Kleidon, 1994). However, we include NASDAQ firms since we normalize CO by average trading volume, which cancels out the effect of double counting.[6] Finally, we eliminate stocks whose past returns, trading volumes, or prices during the formation period are missing, along with stocks whose prices as of the portfolio formation date were less than a dollar.

We obtain the book value of equity from the Compustat database and use it to calculate the book-to-market ratios. We compute a firm's book-to-market ratio using the market value of its equity at the end of December of the previous year and the book value of common equity plus balance-sheet deferred taxes for the firm's latest fiscal year ending in the prior calendar year, following Fama and French (1992). Tests that require the book-to-market ratio (e.g., book-to-market-adjusted returns and cross-sectional regressions) are based on the subset of firms in the Compustat database. Panel A of Table 1 reports descriptive statistics of the CO measure. Panel B of Table 1 reports for each CO decile the time-series average of the median values within each month of the market capitalization (SIZE), the book-to-market ratio (BM), the market beta (BETA), the return over the previous 12 months (MOM), the current month's return (REV), the illiquidity measure (ILLIQ), the idiosyncratic volatility (IVOL), the turnover (TURN), and the unrealized capital gain (UCG). These variables are defined in Appendix B. Panel C reports the time-series average of cross-sectional correlations.

[6]For robustness, we have tried an alternative method for sample selection following Lee and Swaminathan (2000). We find that the results are almost identical when we include only NYSE and AMEX stocks whose prices are greater than one dollar.

Panel B of Table 1 shows that stocks in higher CO deciles tend to be more liquid and have higher values of book-to-market ratios, beta, momentum, and unrealized capital gain. SIZE, REV, IVOL, and TURN do not show monotonic patterns across CO deciles, but the correlation matrix in Panel C shows that SIZE, REV, and TURN are positively correlated with CO (the correlation coefficients are 0.005, 0.01, 0.041, respectively) while IVOL is negatively correlated with CO (correlation coefficient: $-0.098$). As expected, the previous return variable (MOM) shows a strong positive relation to CO (correlation coefficient: 0.554). We control for the effect of momentum using a few alternative methods in Section 4, and we also conduct cross-sectional regressions to control for the effect of various stock characteristics on returns.

[**Table 1 about here**]

## *2.3. Portfolio Formation*

At the beginning of each month $t$, from January 1964 to November 2009, all stocks are ranked on the basis of our CO measure using monthly returns and trading volumes over the previous 12 months ($t-12$ to $t-1$). Based on these rankings, the stocks are assigned to one of ten portfolios. We focus on the monthly returns of the strongest continuing overreaction deciles on the positive side (CO decile 10) and the strongest continuing overreaction deciles on the negative side (CO decile 1) over the next $K$ months ($t+1$ to $t+K$). By excluding returns and volumes in month $t$, we impose a one-month gap between the portfolio formation period and the holding period ($K$) to reduce the effect of negative autocorrelation in monthly returns (see Jegadeesh, 1990). Following Jegadeesh and Titman (1993), we construct overlapping portfolios to increase the power of the tests. Under this strategy, the monthly return for a $K$-month holding period consists of monthly returns from strategies implemented in the previous $K$ months. For instance, a December portfolio return for a three-month holding period is an equal-weighted average of the first month return from a strategy implemented in November, the second month return from October, and the third month return from September. This method is approximately equal to substituting one of the three portfolios every month and carrying over the remaining two portfolios from the previous month. By means of this method, we use simple $t$-statistics to test whether or not the returns of our strategies are significantly different from zero.

# 3. Continuing Overreaction and the cross-section of stock returns

## *3.1. Portfolio-level Analysis*

Panel A of Table 2 presents the equal-weighted and value-weighted average monthly returns over the next $K$ months ($K = 3, 6, 9, 12$) for the period from January 1965 to December 2009. Each portfolio is formed by sorting NYSE/AMEX/NASDAQ stocks based on the CO measure calculated over the past 12 months. Portfolio 1 (downward continuing overreaction) comprises stocks with the lowest values of CO and portfolio 10 (upward continuing overreaction) comprises stocks with the highest values of CO. Panel A of Table 2 shows a monotonic relation between the CO ranks and the portfolio returns. That is, stocks that are likely to have experienced strong downward continuing overreaction show the lowest returns, and stocks that are likely to have experienced strong upward continuing overreaction exhibit the highest returns.

[**Table 2 about here**]

Panel A of Table 2 also reports the average monthly returns of zero-investment portfolios that long the upward continuing overreaction portfolios (portfolio 10) and short the downward continuing overreaction portfolios (portfolio 1). The returns of all zero-investment portfolios are positive and statistically significant. For the 3- and 6-month holding periods, the average monthly returns of this strategy are 1.10% and 0.99% respectively for the equal-weighted portfolios, and 0.80% and 0.82% respectively for the value-weighted portfolios. These results indicate that profitable long-short trading strategies can be implemented using a measure of continuing overreaction, with annualized returns between 10% and 14% before transaction costs. The long-short portfolios are less profitable with longer holding periods, but are still statistically and economically significant; the average monthly returns are 0.57% for the equal-weighted portfolios and 0.59% for the value-weighted portfolios for the 12-month holding period.

### *3.2. Risk Adjustments*

We employ two different methods to examine whether the result is just a compensation for bearing risk: Fama-French alphas and benchmark-adjusted returns. Panel B of Table 2 reports the Fama-French three-factor alphas from the regression of the equal- and value-weighted portfolio returns on a constant, the excess market return, a size factor (SMB), and a book-to-market factor (HML), following Fama and French (1993).[7] The alphas can be interpreted as the risk-adjusted returns relative to the three-factor model. We find that the alphas of hedge portfolios that long the highest CO portfolios and short the lowest CO portfolios are larger than the raw return differences in Panel A of Table 2. For example, the alphas of the hedge portfolios are 1.16% (equal-weighted) and 0.93% (value-weighted) for 6-month holding periods, which are larger than the raw returns of 0.99% and 0.82% in Panel A of Table 2.

We also examine benchmark-adjusted returns of CO portfolios. Each firm's monthly benchmark-adjusted return is computed by subtracting the monthly equal-weighted return of the appropriate benchmark portfolio from the individual stock's monthly return. The benchmark portfolios are constructed yearly at the end of June based on the market capitalization at the end of June using the NYSE size breakpoints and the book equity at the last fiscal year end of the prior calendar year divided by market value of equity at the end

[7]Fama-French three-factors are from Ken French's Web site.

of December of the prior year. Table 3 presents equal-weighted average monthly returns when size-adjusted returns, book-to-market-adjusted returns, and size and book-to-market-adjusted returns are used instead of raw returns. For size or book-to-market adjusted returns, we construct 10 size or book-to-market benchmark portfolios. For size and book-to-market adjusted returns, we construct 25 size-B/M benchmark portfolios. Compared to Panel A of Table 2, the benchmark-adjusted returns of zero-investment strategies are slightly lower than the raw returns, but are still statistically and economically significant. The monotonic relation between the returns and the CO ranks also remains strong.

[**Table 3 about here**]

### *3.3. Sub-sample Analyses*

We conduct a bivariate portfolio-level analysis to compare the effect of continuing overreaction between sub-samples. After partitioning all stocks into five groups based on size or book-to-market, within each size/book-to-market group we sort the stocks into ten equal-weighted portfolios according to their 12-month CO measure. This procedure produces portfolios with dispersion in the CO measure but with similar levels of size or book-to-market. Table 4 presents the average returns and alphas of 50 double-sorted portfolios based on size/book-to-market and CO. The results show that the profitability of continuing overreaction strategies is not driven by a subset of firms, as they are profitable for all size and book-to-market subsamples. In every size and book-to-market quintile, the average returns of CO portfolios increase monotonically with their CO decile ranks and the long-short strategies of buying the top CO decile and shorting the bottom CO decile generate statistically and economically significant profits.

There is some evidence in Table 4 that the profits of the CO strategies are larger among small or low book-to-market firms, but they are not monotonic across book-to-market quintiles as the lowest and highest book-to-market quintiles have higher alphas than the middle quintiles.

**[Table 4 about here]**

# 4. Momentum and Continuing Overreaction

Since Jegadeesh and Titman (1993), the momentum anomaly has become one of the most famous anomalies in the stock market. On the international front, Rouwenhorst (1998, 1999) and Griffin, Ji, and Martin (2003) show that the momentum strategy also generates significant positive profits in European, emerging, and international markets, respectively. This simple and significantly profitable strategy is recognized as one of the biggest challenges to financial economists and a number of hypotheses have been advanced to explain momentum profits.

By construction, our CO measure is positively correlated with momentum. For instance, if every monthly return of a particular stock is positive over the previous 12 months, the stock is likely to be included in higher CO deciles and is also likely to be in the winner portfolio. Thus, we examine whether our results are due to stock price momentum in this section.

First, we calculate benchmark-adjusted returns of one strategy using the returns of the portfolios formed by the other strategy as a benchmark. For example, when computing the momentum-adjusted returns of CO portfolios, the return of each stock is adjusted by the equal-weighted return of the momentum decile where the stock belongs. We also construct double-sorted portfolios based on the two strategies. Lastly, firm-level cross-sectional regressions are estimated with CO and momentum simultaneously included as independent variables.

In Table 5, the average raw returns of zero-investment portfolios for the 6-month holding period are 0.99% and 0.95% per month for the CO and momentum strategies, respectively. However, the $t$-statistic of the CO profits is much higher than that of momentum (6.09

and 3.66, respectively), which means that the CO strategies have higher Sharpe ratios. Of greater importance here are the momentum-adjusted CO returns and the CO-adjusted momentum returns. Although the differences between portfolio 10 and portfolio 1 of these two benchmark-adjusted returns are very similar, the patterns of portfolio returns are surprisingly different. The momentum-adjusted returns of the CO portfolios still show a monotonic increase across the CO deciles and they are statistically significant in the bottom four and top three deciles. However, except for the loser portfolio (momentum decile 1), the CO-adjusted momentum returns do not differ much across momentum deciles and are not statistically different from zero. Put differently, most of the momentum profits are generated by the loser portfolio once the effect of continuing overreaction is taken into account. This finding is related to previous studies on momentum. Eisdorfer (2008) finds that approximately 40% of the momentum profit comes from delisting returns, and most of the delisting-profit is derived from bankrupt firms. He shows that 84.1% of delistings in the loser portfolio are due to bankruptcy. Agarwal and Taffler (2008) also find that more than half of the bankrupt firms belong to the lowest momentum quintile in their sample. This dependence on bankrupt firms reduces the economic significance of momentum profits; investors may not be able to earn profits generated by the delisting returns since all short positions should be closed out before the delisting day (Eisdorfer, 2008).

[**Table 5 about here**]

Figure 1 demonstrates that a significant proportion of firms delisted for poor performance are in the loser portfolio, whereas the downward CO portfolios contain relatively smaller proportions of bankrupt firms. The results suggest that, unlike momentum profits, the returns of our CO strategies are less likely to be driven by the extreme negative returns of the poor-performance delists.[8]

[**Figure 1 about here**]

[8]In our sample, the average delisting return for poor-performance delists is −31%.

We also restrict our sample to the years from 1980 to 2009 to compare the profits of momentum and CO strategies in more recent years, and present the results in Panel B of Table 5 and Figure 2. We find that all the CO-adjusted returns of the momentum portfolios are insignificant except for the loser portfolio, and moreover, there is no clear monotonic pattern across the momentum portfolios. The difference between the winner and loser portfolios in their CO-adjusted returns is not statistically significant during this period; however, the continuing overreaction strategies show highly significant momentum-adjusted returns.

[**Figure 2 about here**]

Figure 3 shows the returns of momentum and CO portfolios in three sub-periods (1965–1979, 1980–1994, and 1995–2009). In the most recent 15-year period, as Figure 3 shows, there is no clear monotonic increase in returns across momentum portfolios, and the return difference between the winner and loser portfolios is statistically insignificant. This result can be partly attributed to the momentum "crashes" described in Daniel and Moskowitz (2011), who show infrequent but strong negative returns of momentum strategies including those in March–May of 2009. On the other hand, the returns of our CO portfolios monotonically increase with CO deciles in all sub-periods and the return difference between upward and downward CO portfolio is statistically significant at the 5% level even in recent years (unreported). Moreover, the value-weighted cumulative return of CO strategies during 2009 is $-10.85\%$, compared to $-68.39\%$ of momentum strategies. In short, our continuing overreaction strategies appear to be more robust across sub-periods compared to the momentum strategies.

[**Figure 3 about here**]

We construct double-sorted portfolios in two ways to further explore the relation between continuing overreaction and momentum. In Panel A of Table 6, stocks are first sorted into quintiles based on their cumulative return from month $t-12$ through $t-1$ (momentum). Then within each momentum quintile, we sort the stocks into ten portfolios according to the 12-month CO measure. Panel B of Table 6 reverses the sort order. Panel A shows that all CO profits are significant for each given momentum quintile. On the other hand, only half of momentum profits in Panel B are significant within each CO quintile. The results indicate that, compared to past returns, CO is a more robust predictor of the cross-section of stock returns. The double sorts also provide more profitable strategies. For value-weighted portfolios, the average monthly return of strategy that buys winner-upward CO portfolios and sells loser-downward CO portfolios is 1.52% when stocks are first sorted on momentum. This average monthly profit increases to 1.84% when stocks are first sorted on CO. The corresponding $t$-statistics are all above 4 (unreported).

**[Table 6 about here]**

We next conduct a firm-level cross-sectional analysis using the Fama and MacBeth (1973) procedure. We run the following cross-sectional regression with 6-month buy-and-hold returns:

$$
\begin{aligned}
r_{i,t+1,t+6} = {} & \lambda_{0,t} + \lambda_{1,t}\mathrm{CO}_{i,t} + \lambda_{2,t}\mathrm{MOM}_{i,t} + \lambda_{3,t}\mathrm{BETA}_{i,t} + \lambda_{4,t}\mathrm{SIZE}_{i,t} + \lambda_{5,t}\mathrm{BM}_{i,t} \\
& + \lambda_{6,t}\mathrm{REV}_{i,t} + \lambda_{7,t}\mathrm{ILLIQ}_{i,t} + \lambda_{8,t}\mathrm{IVOL}_{i,t} + \lambda_{9,t}\mathrm{TURN}_{i,t} + \lambda_{10,t}\mathrm{UCG}_{i,t} + \epsilon_{i,t+1,t+6}
\end{aligned}
\tag{3}
$$

where $r_{i,t+1,t+6}$ is the 6-month return on stock $i$ from month $t+1$ to month $t+6$, $\mathrm{CO}_{i,t}$ is the continuing overreaction measure, $\mathrm{MOM}_{i,t}$ is the cumulative return over the previous 12 months, $\mathrm{BETA}_{i,t}$ is the market beta, $\mathrm{SIZE}_{i,t}$ is the natural logarithm of the market capitalization, $\mathrm{BM}_{i,t}$ is the book-to-market ratio in month $t$,[9] $\mathrm{REV}_{i,t}$ is the reversal variable defined as the return on the stock in month $t$, $\mathrm{ILLIQ}_{i,t}$ is the illiquidity measure following Amihud (2002), $\mathrm{IVOL}_{i,t}$ is the idiosyncratic volatility in month $t$, $\mathrm{TURN}_{i,t}$ is the average monthly turnover over the previous 12 months (from month $t-12$ to month $t-1$), and $\mathrm{UCG}_{i,t}$ is the unrealized capital gains following Grinblatt and Han (2005). Detailed descriptions of

[9]Following Fama and French (1992), the book-to-market ratios are winsorized at the 0.5% and 99.5% levels in order to minimize the effect of outliers.

each variable are in Appendix B.

Table 7 reports the time-series averages of the slope coefficients, along with the corresponding Newey and West (1987) adjusted $t$-statistics. The univariate regression result shows a positive and statistically significant relation between CO and the cross-section of future stock returns. The average slope of the CO measure alone is 0.060 with a $t$-statistic of 6.12. In the regression of 6-month return on momentum, the average slope coefficient of the momentum variable is positive and statistically significant, but the magnitude and significance are lower than those of CO (0.028, with a $t$-statistic of 2.83). When both CO and the momentum variable are added to the regression, the momentum variable is insignificant while CO becomes more significant. Even after other control variables are included in Model (4), CO is the strongest determinant of stock returns.

[**Table 7 about here**]

Through a series of tests, we show that the profits of our continuing overreaction strategies are not driven by momentum. Our results provide direct support for DHS; not only investor continuing overreaction explains the momentum effect, but also it has a better explanatory power than momentum for the cross-section of stock returns. The empirical results corroborate the simulation results in Appendix A.

Lastly, we examine whether the returns of CO strategies exhibit long-term reversals since DHS argue that investor overconfidence and biased self-attribution lead to long-term reversals as well as short-term momentum. Figure 4 shows the average cumulative returns of zero-investment strategy that buys the top CO decile and sells the bottom CO decile for the next 60 months. The portfolio returns exhibit a positive drift up to about one year after formation and the returns reverse thereafter. This return reversal is more prominent in the equal-weighted portfolios. The evidence presented in Figure 4 indicates that short-term return predictability based on our CO measure is likely to be the result of investor continuing overreaction, which eventually corrects in the long term.

**[Figure 4 about here]**

# 5. Return Consistency, Information Discreteness, and Continuing Overreaction

Grinblatt and Moskowitz (2004) study the role of return consistency in momentum profits and find that the consistency of past returns plays an important role in the cross-section of expected returns. Da et al. (2012) develop a measure of information discreteness (ID) that captures whether the flow of information during the formation period was continuous or discrete using the sign of daily return, and find that continuous information induces stronger return continuation. In this section, we test whether the continuing overreaction effect is due to the effects of return consistency or information discreteness since stocks with a series of returns in the same direction tend to be included in extreme CO deciles and also likely to have high levels of return consistency and low levels of information discreteness.[10]

Grinblatt and Moskowitz (2004) introduce the return consistency dummies, PosRC and NegRC. For stocks with positive (negative) past 12 month returns, PosRC (NegRC) takes a value of one if the stock has experienced positive (negative) monthly returns for at least eight of the past twelve months. Since our CO measure also uses the sign of monthly returns, it may capture the effect of return consistency, or more generally, that of the number of positive return months and the number of negative return months. If the monthly trading volume was constant over the past 12 months and if we used the same weight for all months, our CO measure would take a value equal to the difference between the number of months with positive returns and the number of months with negative returns.

To address whether the profits of continuing overreaction strategies are driven by return consistency and more generally by the number of months with positive versus negative

[10]The correlation coefficients of the absolute value of CO against RC and ID are 0.3828 and −0.0570, respectively.

returns, we form double-sorted portfolios based on the CO measure and the number of positive return months minus the number of negative return months (Npos_neg) in Panel A of Table 8. We find that buying the highest CO quintile and selling the lowest CO quintile generates statistically significant profits for both equal- and value-weighted portfolios within each quintile formed by Npos_neg. Therefore, it does not appear that CO is merely capturing the effect of the number of months with positive versus negative returns.

[**Table 8 about here**]

Next, we form double-sorted portfolios based on continuing overreaction and information discreteness. Da et al. (2012) propose signed versions of information discreteness measure, PosID and NegID. PosID (NegID) takes a value of the percentage of positive (negative) return days minus that of negative (positive) return days during the formation period when the past 12-month return (MOM) is positive (negative). Although the information discreteness measure is constructed using daily returns while our CO measure uses monthly returns, we also address whether our CO measure captures the effect of information discreteness. In Panel B of Table 8, stocks with negative (positive) past returns are sorted into three groups by NegID (PosID) measure. In this way, stocks are assigned to one of six ID groups. Within each ID group, stocks are sorted into quintiles according to the CO measure. Due to the way PosID and NegID measures are defined, we exclude stocks with zero 12-month past returns, which account for about 0.5% of the total sample. Panel B of Table 8 shows that the profits of the continuing overreaction strategies are statistically significant in every ID group. These results show that information discreteness does not fully explain the effect of continuing overreaction.

We also perform Fama-MacBeth cross-sectional regressions of stock returns on CO, return consistency dummy variables (PosRC, NegRC), the number of months with positive returns minus the number of months with negative returns (Npos_neg), information discreteness

(PosID, NegID), and other control variables.

$$
\begin{aligned}
r_{i,t+1,t+6} = {} & \lambda_{0,t} + \lambda_{1,t}\text{CO}_{i,t} + \lambda_{2,t}\text{MOM}_{i,t} + \lambda_{3,t}\text{PosID}_{i,t} + \lambda_{4,t}\text{NegID}_{i,t} \\
& + \lambda_{5,t}\text{PosRC}_{i,t} + \lambda_{6,t}\text{NegRC}_{i,t} + \lambda_{7,t}\text{Npos\_neg}_{i,t} + \lambda_{8,t}\text{BETA}_{i,t} \\
& + \lambda_{9,t}\text{SIZE}_{i,t} + \lambda_{10,t}\text{BM}_{i,t} + \lambda_{11,t}\text{REV}_{i,t} + \lambda_{12,t}\text{ILLIQ}_{i,t} \\
& + \lambda_{13,t}\text{IVOL}_{i,t} + \lambda_{14,t}\text{TURN}_{i,t} + \lambda_{15,t}\text{UCG}_{i,t} + \epsilon_{i,t+1,t+6} \qquad (4)
\end{aligned}
$$

The Fama-Macbeth regression estimates are reported in Table 9. We find that CO remains as a highly significant determinant of the cross-sectional returns after inclusion of the additional variables.

**[Table 9 about here]**

# 6. An Alternative Measure of Continuing Overreaction

Odean (1998) shows that the most robust effect of overconfidence is high trading volume, therefore we use trading volume when we construct a measure of investor continuing overreaction. For robustness, we examine whether an alternative measure of continuing overreaction also predicts future returns. Daniel et al. (1998) and Odean (1998) show a positive relation between overconfidence and volatility, therefore we construct an alternative CO measure using idiosyncratic volatility, $\text{CO}_{IVOL}$. $\text{CO}_{IVOL}$ is constructed in an analogous manner to CO by replacing trading volume ($vol_{i,t}$) with idiosyncratic volatility ($\text{IVOL}_{i,t}$) in equations (1) and (2).[11] Table 10 presents raw and risk-adjusted returns for portfolios based on the 12-month $\text{CO}_{IVOL}$. The alternative measure of continuing overreaction based on idiosyncratic volatility ($\text{CO}_{IVOL}$) also exhibits a monotonic relation with the portfolio returns and the returns of the hedge portfolios are comparable to those using the CO measure based

[11]Idiosyncratic volatility is more likely to capture price fluctuations due to private information, which is subject to the effect of overconfidence. We also conduct our tests with an alternative CO measure using total volatility and find similar results.

on trading volume. For example, the three-factor alpha of the hedge portfolio (long decile 10, short decile 1) based on $CO_{IVOL}$ is 1.34% ($t$-stat: 7.19) for the equal-weighted portfolio, and 0.92% ($t$-stat: 4.62) for the value weighted portfolio, while those based on CO are 0.99% ($t$-stat: 6.09) for the equal-weighted portfolio and 0.82% ($t$-stat: 4.20) for the value-weighted portfolio (Table 2).

Table 11 reports the Fama-MacBeth cross-sectional regression estimation results using $CO_{IVOL}$. These results also show that an alternative measure of continuing overreaction has significant explanatory power with respect to the cross-section of the stock returns. Similar to the results for CO in Table 9, $CO_{IVOL}$ subsumes the momentum effect, and remains as a strong predictor of future returns after we include a host of control variables. Overall, the results presented in Tables 10 and 11 provide additional support to our argument that a measure of continuing overreaction predicts future returns as implied by DHS.

[**Table 10 and 11 about here**]

# 7. Conclusion

A growing body of literature argues that investor overconfidence can explain several anomalous patterns in stock returns. In particular, Daniel et al. (1998) build a theory of stock market underreactions and overreactions based on overconfidence and biased self-attribution, and a number of empirical studies present supporting evidence of their model.

Motivated by the idea that investor overreaction may underlie stock return predictability, we propose a measure of continuing overreaction using weighted signed volumes and show that it predicts future stock returns. Trading strategies that buy positive continuing overreaction stocks and sell negative continuing overreaction stocks generate significant abnormal returns. In cross-section analyses, we find that our measure of continuing overreaction is positively related to future stock returns, and the results are robust to the control of size, book-to-market, momentum, short-term reversals, liquidity, idiosyncratic volatility, turnover, unrealized capital gain, return consistency, and information discreteness.

By construction, our measure of continuing overreaction is correlated with stock price momentum. Thus, one might argue that the profits of continuing overreaction strategies come from the momentum effect. Our evidence, however, shows that continuing overreaction explains momentum, not vice versa. The continuing overreaction strategies generate significant profits after controlling for momentum, but momentum profits disappear once we account for the effect of continuing overreaction. In addition, compared to the momentum strategies, our continuing overreaction strategies show higher Sharpe ratios and clearer monotonic patterns in portfolio returns even in recent years. We also find similar results using an alternative measure of continuing overreaction constructed from idiosyncratic volatility.

The numerical simulation results using the model of Daniel et al. (1998) also show that measures of continuing overreaction predict future returns and that they are better predictors of future returns than past returns. Overall, our results provide a direct support for the model of Daniel et al. (1998) that investor overreactions due to overconfidence and biased self-attribution drive stock return predictability.

# Appendix A. Numerical Simulation Results

In this section, we present results of numerical simulation based on the model of Daniel et al. (1998, DHS). They derived momentum in their model by simulation, so we follow their approach to show that a measure of continuing overreaction predicts future returns in their model. Below is the description of their dynamic model of outcome-dependent confidence, which can be found in Section III.B of DHS.

There are two types of investors, the informed and the uninformed. The informed are risk neutral and the uninformed are risk averse. Thus, the stock price is set by the risk neutral informed investors as their conditional expectation of the value of the stock.

The unobservable value of a share of the firm's stock is $\tilde{\theta} \sim N(0, \sigma_\theta^2)$. At date 1, each informed investor receives a private signal $\tilde{s}_1 = \tilde{\theta} + \tilde{\epsilon}$, where $\tilde{\epsilon} \sim N(0, \sigma_\epsilon^2)$. At dates 2 through T, a public signal $\tilde{\phi}_t$ is released, $\tilde{\phi}_t = \tilde{\theta} + \tilde{\eta}_t$, where $\tilde{\eta}_t$ is i.i.d. and $\tilde{\eta}_t \sim N(0, \sigma_\eta^2)$. $\sigma_\theta^2$ and $\sigma_\eta^2$ are common knowledge. Let $\Phi_t$ be the average of all public signals through date $t$:

$$\Phi_t = \frac{1}{(t-1)} \sum_{\tau=2}^{t} \phi_\tau = \theta + \frac{1}{(t-1)} \sum_{\tau=2}^{t} \eta_\tau \tag{5}$$

At date 1, the investor believes that the precision of his private signal is $v_{C,1} = 1/\sigma_\epsilon^2$. Therefore, initially the investor is not overconfident and correctly perceives the precision of his private signal. As public information releases, the investor updates his estimate of the precision of his private signal. If the new public confirms the investor's initial private information, and the private signal is not too far away from the public signal, then the investor becomes more confident in his private signal. If the public signal disconfirms his private signal, the investor revises the estimated precision downward, but not by as much.

Thus, the confidence of the investor is updated as follows:

$$\text{if}\begin{cases}\text{sign}(s_1 - \Phi_{t-1}) = \text{sign}(\phi_t - \Phi_{t-1}) \text{ and } |s_1 - \Phi_{t-1}| < 2\sigma_{\Phi,t} \\ \qquad\qquad\qquad\qquad\qquad\qquad \text{then } v_{C,t} = (1+\bar{k})v_{C,t-1} \\ \text{otherwise} \qquad\qquad\qquad\qquad\qquad v_{C,t} = (1-\underline{k})v_{C,t-1}\end{cases} \tag{6}$$

where $\sigma_{\Phi,t}$ is the standard deviation of $\Phi$ at date $t$.

Using $v_\theta = 1/\sigma_\theta^2$ and $v_\eta = 1/\sigma_\eta^2$, the price of the security at date $t$ is given by

$$P_t = \frac{(t-1)v_\eta \Phi_t + v_{C,t}s_1}{v_\theta + (t-1)v_\eta + v_{C,t}}, \quad t = 1, 2, \ldots \tag{7}$$

$v_{C,t}$ is a direct measure of investor overconfidence, therefore we take $v_{C,t}$ as a measure of investor overreaction and construct the continuing overreaction measure in an analogous manner to equations (1) and (2) as follows.

The signed investor confidence at date $t$ is given by:

$$SC_t = \begin{cases} v_{C,t} & \text{if } P_t - P_{t-1} > 0 \\ 0 & \text{if } P_t - P_{t-1} = 0 \\ -v_{C,t} & \text{if } P_t - P_{t-1} < 0 \end{cases} \tag{8}$$

and we define $\text{CO}_{C,t}$ as

$$\text{CO}_{C,t} = \frac{sum(w_J \cdot SC_{t-J}, \cdots, w_1 \cdot SC_{t-1})}{mean(v_{C,t-J}, \cdots, v_{C,t-1})} \tag{9}$$

where $w_j$ is a weight that takes a value of $J - j + 1$ in date $t - j$ (i.e., $w_J = 1$, $w_{J-1} = 2$, and $w_1 = J$).

Since $v_{C,t}$ is unobservable, we also construct a measure of continuing overreaction using trading volume as a proxy for $v_{C,t}$, which mirrors our empirical CO measure. In the model of DHS, the risk-averse uninformed investors trade with the risk-neutral informed investors. Since the demand curve of risk-neutral investors is flat, the market clears at the price equal to the risk-neutral investors' expectation of $\theta$ in equation (7) and the trading volume is determined by the demand of the risk-averse investors.

If the risk-averse uninformed investors form their expectations based only on public signals and choose their demand for the risky asset to maximize a mean-variance utility function with a risk aversion coefficient $A$ whose value is set to one for simplicity, their demand $x_t$ takes the following form:

$$x_t = \frac{E(\theta|\Phi_t) - P_t}{Var(\theta|\Phi_t)}, \tag{10}$$

where

$$E(\theta|\Phi_t) = \frac{(t-1)v_\eta \Phi_t}{v_\theta + (t-1)v_\eta}, \tag{11}$$

$$Var(\theta|\Phi_t) = \frac{1}{v_\theta + (t-1)v_\eta}. \tag{12}$$

Since there are only two types of investors, the date $t$ trading volume can be written as the absolute change in the demand of the uninformed.

$$vol_t = |x_t - x_{t-1}| \tag{13}$$

Using $vol_t$ instead of $v_{C,t}$ in equations (8) and (9), we construct the $\mathrm{CO}_{vol,t}$ measure.

For the simulation, we use the same parameter values used by DHS, $\bar{k} = 0.75$, $\underline{k} = 0.1$, $\sigma_\theta^2 = \sigma_\epsilon^2 = 1$, and $\sigma_\eta^2 = 7.5$.[12] We perform this simulation 1,000,000 times, each time redrawing the value $\theta$, the private signal $s_1$, and the public signals $\tilde{\phi}_t$.

We employ a trading strategy of holding the stock for six periods ($K = 6$) based on the measure of continuing overreaction over the past six periods ($J = 6$), because the price reverses around t=16 using those parameter values (Figure 2 of DHS). We also impose a one-period gap between the portfolio formation period and the holding period. Therefore,

[12] Although the simulation results of DHS use this set of parameter values, we find that a wide range of parameter values give similar patterns of momentum and reversals that roughly match the time-scale of the empirical results and that our results hold using those parameter values.

Table A.1: Average Future Returns of CO Portfolios Simulated from the DHS Model

| | Average Future Returns | |
|---|---|---|
| Portfolio | $CO_C$ | $CO_{vol}$ |
| 1 (Downward CO) | −0.0410 | −0.0330 |
| 2 | −0.0203 | −0.0200 |
| 3 | −0.0004 | 0.0004 |
| 4 | 0.0203 | 0.0199 |
| 5 (Upward CO) | 0.0407 | 0.0322 |

we examine future stock returns defined as the price change following DHS, $P_{i,14} - P_{i,8}$, conditional on a measure of continuing overreaction constructed from investor confidence or trading volume from $t = 2$ to $t = 7$ ($CO_{C,8}$ or $CO_{vol,8}$).[13] 1,000,000 future return draws are divided into five portfolios based on the two CO measures and we present the average future returns in Table A.1.

Table A.1 shows a positive relationship between the ranks of each CO measure and the average future returns. The correlation between the two CO measures is 0.7809, indicating that an empirical measure of continuing overreaction based on trading volume is a good proxy of the degree of continuing overreaction directly computed from the level of investor overconfidence.

We also conduct Fama-MacBeth regressions of future returns on the CO measure and the past return variable (MOM) defined as $P_{i,7} - P_{i,1}$. To match our empirical tests, we draw 5,000 observations for each regression, and we conduct a total of 500 regressions (we have 534 months in our empirical analysis). To evaluate the economic significance of each variable, we normalize each variable by its standard deviation. Thus the regression coefficient measures the effect of one standard deviation change in the independent variable on future returns. Table A.2 reports the average regression coefficients and their $t$-statistics.

We find that the continuing overreaction measure, either constructed from investor confidence ($CO_C$) or trading volume ($CO_{vol}$), has a bigger impact on future returns than past

[13]This requires the price information from $t = 1$ to $t = 7$.

Table A.2: Fama-MacBeth Regressions of Future Returns on CO and Momentum Simulated from the DHS Model

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| $\mathrm{CO}_C$ | 0.0825 | | 0.0814 | | 0.0812 | |
| | (115.27) | | (109.41) | | (110.09) | |
| $\mathrm{CO}_{vol}$ | | 0.0656 | | 0.0645 | | 0.0647 |
| | | (81.47) | | (80.41) | | (80.45) |
| sign(MOM)$\cdot v_{C,7}$ | | | 0.0053 | 0.0173 | | |
| | | | (9.57) | (33.67) | | |
| sign(MOM)$\cdot mean(v_C)$ | | | | | 0.0097 | 0.0182 |
| | | | | | (13.63) | (26.62) |
| MOM | 0.0365 | 0.0485 | 0.0339 | 0.0386 | 0.0307 | 0.0367 |
| | (42.02) | (53.08) | (33.92) | (35.02) | (28.68) | (31.59) |

returns as shown in Columns (1) and (2) of Table A.2. Thus, the result from the simulation is in line with our empirical results. As expected, the direct continuing overreaction measure, $\mathrm{CO}_C$, has a stronger explanatory power than the proxy measure, $\mathrm{CO}_{vol}$.

Also, we examine whether the effect of continuing overreaction – the *increasing trend* in overconfidence – is subsumed by that of the simple *level* of overconfidence. DHS show that what drives momentum is not overconfidence per se, but continuing overreaction from biased self-attribution. Thus, we control for the effect of overconfidence itself by adding each of the following two variables, the level of overconfidence at the end of the formation period $v_{C,7}$ and the average level of overconfidence over the formation period $mean(v_C)$=mean($v_{C,2}, ..., v_{C,7}$). These variables are multiplied by the sign of past return variable (MOM) to reflect the direction of overconfidence. Columns (3) through (6) of Table A.2 show that the directional overconfidence measures, sign(MOM)$\cdot v_{C,7}$ and sign(MOM)$\cdot mean(v_C)$, have some predictive power over future returns, but they have much weaker effects compared to the continuing overreaction measures. Therefore, the results confirm that the major contributor to the return predictability in the model of DHS is continuing overreaction rather than the level of overconfidence.

# Appendix B. Variable Definitions

| Variable | Description |
|---|---|
| $\text{CO}_t$ | The measure of continuing overreaction $$\text{CO}_t = \frac{sum(w_1 \cdot SV_{t-1}, \cdots, w_J \cdot SV_{t-J})}{mean(vol_{t-1}, \cdots, vol_{t-J})}$$ where $$SV_t = \begin{cases} vol_t & \text{if } r_t > 0 \\ 0 & \text{if } r_t = 0 \\ -vol_t & \text{if } r_t < 0 \end{cases}$$ $vol_t$ is the dollar volume in month $t$ and $r_t$ is the stock return in month $t$. |
| $\text{BETA}_t$ | The market beta estimated for each stock by regressing its daily excess returns in month $t$ on market excess returns. We use the CRSP value-weighted index return as the market return and T-bill rates as the risk-free rate. |
| $\text{SIZE}_t$ | The firm size defined as the natural logarithm of the market capitalization at the end of month $t$. |
| $\text{BM}_t$ | The book-to-market ratio in month $t$, defined as the ratio of the book value of common equity plus balance-sheet deferred taxes for the firm's latest fiscal year ending in the prior calendar year to the market value of its equity at the end of December of the previous year following Fama and French (1992). |
| $\text{REV}_t$ | The reversal variable defined as the return on the stock in month $t$ following Jegadeesh (1990) and Lehmann (1990). |
| $\text{ILLIQ}_t$ | The illiquidity measure defined as the average ratio of the daily absolute return to the dollar trading volume in month $t$ following Amihud (2002). $$ILLIQ_t = 1/D_t \sum_{d=1}^{D_t} \lvert R_{t,d} \rvert / VOLD_{t,d}$$ where $D_t$ is the number of days in month $t$, $R_{t,d}$ is the return on day $d$ of month $t$, and $VOLD_{t,d}$ is the dollar trading volume on day $d$ of month $t$. |
| $\text{IVOL}_t$ | The idiosyncratic volatility in month $t$, defined as the standard deviation of residuals from a single factor model calculated from daily returns during the month, following Bali, Cakici, and Whitelaw (2011). |
| $\text{TURN}_t$ | The average monthly turnover over the previous 12 months from month $t-12$ to month $t-1$. |

| Variable | Description |
|---|---|
| $\text{MOM}_t$ | The momentum variable defined as the cumulative return over the previous 12 months from month $t-12$ to month $t-1$ excluding month $t$. |
| $\text{PosID}_t/\text{NegID}_t$ | Signed versions of information discreteness measure (ID) following Da et al. (2012): $$\text{PosID}_t = \begin{cases} \%pos - \%neg & \text{if } \text{r}_{t-12,t-1} > 0 \\ 0 & \text{otherwise} \end{cases}$$ $$\text{NegID}_t = \begin{cases} \%neg - \%pos & \text{if } \text{r}_{t-12,t-1} < 0 \\ 0 & \text{otherwise} \end{cases}$$ where $\%pos$ and $\%neg$ denote the percentage of days during the formation period (from month $t-12$ to month $t-1$) with positive and negative returns, respectively, and $r_{t-12,t-1}$ is the return over month $t-12$ to $t-1$. |
| $\text{PosRC}_t/\text{NegRC}_t$ | The positive/negative return consistency dummy variables. $\text{PosRC}_t$ ($\text{NegRC}_t$) takes a value of one if the stock has experienced positive (negative) monthly returns for at least eight of twelve months during the formation period (from month $t'12$ to month $t'1$) and also the previous 12 month returns (MOM) is positive (negative), following Grinblatt and Moskowitz (2004). |
| $\text{Npos\_neg}_t$ | The number of positive return months minus the number of negative return months over the past 12 months from month $t-12$ to month $t-1$. |
| $\text{UCG}_t$ | The unrealized capital gain variable in month $t$ following Grinblatt and Han (2005), defined as: $$UCG_t = \frac{P_{-2} - R_{-1}}{P_{-2}}$$ where $P_{-2}$ is the price at the end of second to last week of the month $t$, and $$R_{-1} = \frac{1}{k}\sum_{n=1}^{260}\left(V_{-1-n}\prod_{\tau=1}^{n-1}[1 - V_{-1-n+\tau}]\right)P_{-1-n}$$ with $k$ a constant that makes the weights on past prices sum to one, and $V-j$ a weekly turnover at previous $j$ week from the end of month $t$. For stocks that have less than five years of historical data from CRSP, we use all available data up to month $t$. |

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# Table 1. Summary Statistics

Panel A reports summary statistics for the continuing overreaction (CO) measure. Panel B reports for each CO decile the time-series average of the median values within each month for the CO measure, the market capitalization (SIZE), the book-to-market ratio (BM), the market beta (BETA), the previous 12-month return (MOM), the one-month reversal variable (REV), the illiquidity measure (ILLIQ), the idiosyncratic volatility (IVOL), the turnover (TURN), and the unrealized capital gains (UCG). These variables are defined in Appendix B. Panel C presents time-series averages of cross-sectional correlations of the variables.

Panel A: Summary statistics

| | | | Percentiles | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | 1% | 5% | 10% | 25% | 50% | 75% | 90% | 95% | 99% |
| CO | 13.00 | 31.56 | −51.49 | −34.02 | −24.84 | −9.12 | 10.30 | 32.62 | 54.98 | 69.25 | 97.23 |

Panel B: Summary statistics for decile portfolios of stocks sorted by CO.

| Decile | CO | SIZE($\$10^6$) | BM | BETA | MOM | REV | ILLIQ($10^5$) | IVOL | TURN | UCG |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | −30.61 | 90.13 | 0.673 | 0.63 | −0.24 | 0.005 | 0.071 | 0.026 | 0.45 | −0.317 |
| 2 | −15.60 | 102.63 | 0.681 | 0.68 | −0.16 | 0.003 | 0.056 | 0.026 | 0.51 | −0.234 |
| 3 | −6.46 | 109.40 | 0.691 | 0.69 | −0.09 | 0.002 | 0.050 | 0.025 | 0.52 | −0.173 |
| 4 | 1.10 | 119.32 | 0.702 | 0.70 | −0.03 | 0.002 | 0.043 | 0.024 | 0.52 | −0.123 |
| 5 | 8.14 | 129.13 | 0.711 | 0.71 | 0.03 | 0.002 | 0.039 | 0.023 | 0.52 | −0.074 |
| 6 | 15.20 | 139.34 | 0.720 | 0.70 | 0.09 | 0.003 | 0.034 | 0.022 | 0.51 | −0.029 |
| 7 | 22.76 | 149.74 | 0.738 | 0.72 | 0.16 | 0.003 | 0.030 | 0.022 | 0.51 | 0.011 |
| 8 | 31.50 | 157.64 | 0.749 | 0.72 | 0.24 | 0.004 | 0.027 | 0.021 | 0.50 | 0.057 |
| 9 | 43.00 | 162.78 | 0.772 | 0.73 | 0.35 | 0.005 | 0.026 | 0.022 | 0.50 | 0.104 |
| 10 | 63.80 | 132.97 | 0.810 | 0.78 | 0.61 | 0.004 | 0.024 | 0.024 | 0.54 | 0.170 |

Panel C: Time-series average of cross-sectional correlations

| | CO | SIZE | BM | BETA | MOM | REV | ILLIQ | IVOL | TURN | UCG |
|---|---|---|---|---|---|---|---|---|---|---|
| CO | 1 | | | | | | | | | |
| SIZE | 0.005 | 1 | | | | | | | | |
| BM | 0.029 | −0.062 | 1 | | | | | | | |
| BETA | 0.032 | 0.045 | −0.061 | 1 | | | | | | |
| MOM | 0.554 | 0.017 | 0.009 | 0.063 | 1 | | | | | |
| REV | 0.010 | 0.005 | 0.012 | 0.035 | 0.015 | 1 | | | | |
| ILLIQ | −0.066 | −0.046 | 0.097 | −0.077 | −0.080 | −0.012 | 1 | | | |
| IVOL | −0.098 | −0.151 | 0.012 | 0.085 | −0.114 | 0.174 | 0.328 | 1 | | |
| TURN | 0.041 | −0.024 | −0.111 | 0.236 | 0.136 | −0.026 | −0.103 | 0.109 | 1 | |
| UCG | 0.356 | 0.088 | −0.032 | 0.040 | 0.440 | 0.159 | −0.245 | −0.410 | 0.007 | 1 |

# Table 2. Returns of Portfolios Based on Continuing Overreaction

Panel A reports average monthly returns in percentages for portfolios based on continuing overreaction (CO) involving NYSE/AMEX/NASDAQ stocks for the period 1965-2009. At the beginning of each month from January 1964 to November 2009, stocks are sorted by the CO measure and divided into ten portfolios. Portfolio 1 (10) comprises stocks with the lowest (highest) values in CO. *K* represents holding periods in months. The monthly return for a *K*-month holding period is the equal-weighted average of returns from strategies implemented in the past *K* months. The numbers in parentheses in Panel A are simple *t*-statistics for monthly returns. Panel B reports the Fama-French three-factor alphas for portfolios based on the CO measure. The last row presents the alphas of hedge portfolios that are long portfolio 10 and short portfolio 1. The numbers in parentheses in Panel B are White's heteroskedasticity-corrected *t*-statistics.

Panel A: Raw Returns

| | Equal-Weighted Portfolios | | | | Value-Weighted Portfolios | | | |
|---|---|---|---|---|---|---|---|---|
| CO Portfolio | $K = 3$ | $K = 6$ | $K = 9$ | $K = 12$ | $K = 3$ | $K = 6$ | $K = 9$ | $K = 12$ |
| 1 (Downward) | 0.54 (2.00) | 0.60 (2.24) | 0.69 (2.60) | 0.80 (3.01) | 0.51 (2.15) | 0.49 (2.11) | 0.51 (2.20) | 0.59 (2.56) |
| 2 | 0.77 (2.82) | 0.84 (3.08) | 0.93 (3.44) | 1.02 (3.75) | 0.71 (3.33) | 0.70 (3.29) | 0.70 (3.31) | 0.73 (3.44) |
| 3 | 0.91 (3.39) | 0.96 (3.58) | 1.03 (3.83) | 1.09 (4.06) | 0.77 (3.68) | 0.75 (3.59) | 0.76 (3.63) | 0.78 (3.70) |
| 4 | 1.00 (3.80) | 1.04 (4.00) | 1.10 (4.22) | 1.15 (4.39) | 0.82 (4.03) | 0.80 (3.91) | 0.81 (3.95) | 0.83 (4.07) |
| 5 | 1.11 (4.25) | 1.15 (4.44) | 1.15 (4.49) | 1.18 (4.58) | 0.86 (4.19) | 0.83 (4.13) | 0.83 (4.11) | 0.83 (4.11) |
| 6 | 1.21 (4.76) | 1.21 (4.75) | 1.21 (4.75) | 1.22 (4.83) | 0.83 (4.07) | 0.85 (4.19) | 0.85 (4.22) | 0.88 (4.35) |
| 7 | 1.30 (5.18) | 1.28 (5.13) | 1.28 (5.10) | 1.26 (5.05) | 0.92 (4.50) | 0.92 (4.62) | 0.95 (4.77) | 0.93 (4.65) |
| 8 | 1.37 (5.51) | 1.37 (5.51) | 1.34 (5.39) | 1.30 (5.26) | 1.01 (5.05) | 1.05 (5.26) | 1.04 (5.20) | 1.00 (5.01) |
| 9 | 1.50 (6.03) | 1.46 (5.85) | 1.42 (5.67) | 1.36 (5.43) | 1.08 (5.24) | 1.12 (5.42) | 1.10 (5.35) | 1.06 (5.18) |
| 10 (Upward) | 1.64 (6.05) | 1.59 (5.85) | 1.49 (5.47) | 1.37 (5.04) | 1.31 (5.62) | 1.31 (5.67) | 1.27 (5.52) | 1.18 (5.15) |
| 10−1 | 1.10 (6.13) | 0.99 (6.09) | 0.79 (5.29) | 0.57 (3.94) | 0.80 (3.71) | 0.82 (4.22) | 0.76 (4.20) | 0.59 (3.44) |

Panel B: Fama-French Three-Factor Alphas

| | Equal-Weighted Portfolios | | | | Value-Weighted Portfolios | | | |
|---|---|---|---|---|---|---|---|---|
| CO Portfolio | $K = 3$ | $K = 6$ | $K = 9$ | $K = 12$ | $K = 3$ | $K = 6$ | $K = 9$ | $K = 12$ |
| 1 (Downward) | −0.73 (−6.18) | −0.68 (−6.00) | −0.60 (−5.56) | −0.51 (−4.85) | −0.41 (−3.13) | −0.46 (−3.90) | −0.47 (−4.16) | −0.42 (−3.86) |
| 2 | −0.51 (−4.93) | −0.45 (−4.41) | −0.36 (−3.66) | −0.29 (−3.03) | −0.20 (−2.10) | −0.23 (−2.69) | −0.25 (−3.11) | −0.24 (−3.14) |
| 3 | −0.35 (−3.65) | −0.31 (−3.39) | −0.25 (−2.87) | −0.20 (−2.34) | −0.11 (−1.45) | −0.14 (−2.00) | −0.16 (−2.32) | −0.17 (−2.46) |
| 4 | −0.25 (−2.94) | −0.21 (−2.46) | −0.15 (−1.87) | −0.11 (−1.40) | −0.06 (−0.96) | −0.10 (−1.67) | −0.10 (−1.78) | −0.09 (−1.67) |
| 5 | −0.13 (−1.81) | −0.09 (−1.18) | −0.08 (−1.13) | −0.06 (−0.86) | −0.02 (−0.44) | −0.05 (−0.98) | −0.06 (−1.24) | −0.07 (−1.43) |
| 6 | −0.01 (−0.13) | −0.01 (−0.18) | −0.01 (−0.22) | 0.00 (0.07) | −0.05 (−1.05) | −0.03 (−0.81) | −0.03 (−0.74) | −0.01 (−0.24) |
| 7 | 0.10 (1.66) | 0.09 (1.50) | 0.08 (1.42) | 0.07 (1.15) | 0.04 (0.79) | 0.05 (1.13) | 0.08 (1.97) | 0.05 (1.32) |
| 8 | 0.19 (3.69) | 0.19 (3.70) | 0.17 (3.09) | 0.14 (2.46) | 0.15 (2.99) | 0.19 (4.31) | 0.18 (4.49) | 0.15 (3.83) |
| 9 | 0.35 (6.23) | 0.31 (5.48) | 0.28 (4.80) | 0.23 (3.71) | 0.21 (2.97) | 0.26 (4.13) | 0.25 (4.31) | 0.22 (4.19) |
| 10 (Upward) | 0.53 (5.84) | 0.48 (5.74) | 0.38 (4.73) | 0.27 (3.45) | 0.46 (3.94) | 0.47 (4.67) | 0.44 (4.88) | 0.35 (4.39) |
| 10−1 | 1.26 (7.03) | 1.16 (7.29) | 0.98 (6.92) | 0.78 (6.01) | 0.86 (3.94) | 0.93 (4.72) | 0.91 (5.00) | 0.77 (4.59) |

# Table 3.
# Benchmark-Adjusted Returns of Portfolios Based on Continuing Overreaction

This table reports benchmark-adjusted and equal-weighted monthly returns for portfolios based on continuing overreaction (CO) using data on NYSE/AMEX/NASDAQ stocks for the period 1965-2009. Portfolio 1 (10) comprises stocks with the lowest (highest) values in CO. *K* represents holding periods in months. The benchmark adjustment is based on equal-weighted portfolios. The benchmark portfolios are formed on the portfolio formation date using all NYSE/AMEX/NASDAQ firms available at the time of portfolio formation. The benchmark-adjusted returns are computed by subtracting the monthly returns of the appropriate benchmark portfolio from the individual stock's monthly returns. The numbers in parentheses are simple *t*-statistics for monthly returns.

| | Size-Adjusted Returns | | | | Book-to-Market-Adjusted Returns | | | | Size and Book-to-Market-Adjusted Returns | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Portfolio | $K = 3$ | $K = 6$ | $K = 9$ | $K = 12$ | $K = 3$ | $K = 6$ | $K = 9$ | $K = 12$ | $K = 3$ | $K = 6$ | $K = 9$ | $K = 12$ |
| 1 | −0.57 | −0.51 | −0.44 | −0.35 | −0.47 | −0.43 | −0.36 | −0.27 | −0.43 | −0.39 | −0.34 | −0.25 |
| (Downward) | (−8.25) | (−7.97) | (−7.36) | (−6.03) | (−6.56) | (−6.65) | (−6.04) | (−4.65) | (−6.67) | (−6.48) | (−6.14) | (−4.77) |
| 2 | −0.34 | −0.28 | −0.21 | −0.14 | −0.29 | −0.25 | −0.18 | −0.11 | −0.27 | −0.22 | −0.16 | −0.10 |
| | (−6.22) | (−5.49) | (−4.26) | (−3.07) | (−5.25) | (−4.97) | (−3.70) | (−2.38) | (−5.32) | (−4.66) | (−3.54) | (−2.32) |
| 3 | −0.21 | −0.17 | −0.12 | −0.08 | −0.19 | −0.15 | −0.10 | −0.06 | −0.18 | −0.13 | −0.09 | −0.05 |
| | (−4.63) | (−4.20) | (−3.39) | (−2.30) | (−4.23) | (−3.90) | (−2.82) | (−1.72) | (−4.36) | (−3.53) | (−2.73) | (−1.69) |
| 4 | −0.12 | −0.09 | −0.05 | −0.02 | −0.1 | −0.09 | −0.05 | −0.02 | −0.09 | −0.07 | −0.04 | −0.02 |
| | (−3.48) | (−2.95) | (−1.84) | (−0.80) | (−2.74) | (−2.86) | (−1.74) | (−0.74) | (−2.73) | (−2.60) | (−1.62) | (−0.66) |
| 5 | −0.02 | 0.00 | 0.00 | 0.01 | −0.03 | −0.01 | −0.01 | 0.00 | −0.04 | −0.01 | −0.02 | 0.00 |
| | (−0.82) | (0.06) | (−0.26) | (0.40) | (−1.26) | (−0.56) | (−0.55) | (0.11) | (−1.68) | (−0.50) | (−1.01) | (−0.25) |
| 6 | 0.08 | 0.06 | 0.04 | 0.05 | 0.06 | 0.04 | 0.03 | 0.04 | 0.05 | 0.03 | 0.02 | 0.03 |
| | (3.60) | (3.52) | (2.90) | (3.23) | (2.56) | (2.36) | (1.85) | (2.52) | (2.23) | (1.91) | (1.45) | (2.15) |
| 7 | 0.16 | 0.13 | 0.11 | 0.09 | 0.14 | 0.11 | 0.09 | 0.07 | 0.12 | 0.10 | 0.08 | 0.06 |
| | (6.33) | (5.83) | (5.40) | (4.42) | (5.05) | (4.77) | (4.13) | (3.32) | (4.76) | (4.52) | (3.85) | (3.14) |
| 8 | 0.22 | 0.20 | 0.16 | 0.12 | 0.17 | 0.17 | 0.14 | 0.09 | 0.14 | 0.14 | 0.11 | 0.08 |
| | (5.90) | (6.00) | (5.23) | (4.16) | (4.49) | (4.86) | (4.13) | (2.96) | (4.24) | (4.67) | (3.90) | (2.82) |
| 9 | 0.34 | 0.27 | 0.23 | 0.17 | 0.29 | 0.25 | 0.21 | 0.15 | 0.26 | 0.21 | 0.17 | 0.12 |
| | (5.74) | (5.12) | (4.61) | (3.54) | (4.77) | (4.59) | (4.11) | (3.03) | (4.72) | (4.34) | (3.79) | (2.75) |
| 10 (Upward) | 0.47 | 0.39 | 0.29 | 0.17 | 0.42 | 0.37 | 0.26 | 0.15 | 0.38 | 0.33 | 0.23 | 0.12 |
| | (4.41) | (4.07) | (3.25) | (2.02) | (3.82) | (3.76) | (2.91) | (1.74) | (3.74) | (3.53) | (2.68) | (1.55) |
| 10−1 | 1.04 | 0.90 | 0.72 | 0.52 | 0.89 | 0.81 | 0.63 | 0.42 | 0.82 | 0.72 | 0.56 | 0.37 |
| | (6.21) | (5.92) | (5.14) | (3.83) | (5.19) | (5.20) | (4.42) | (3.10) | (5.15) | (4.94) | (4.23) | (2.96) |

# Table 4. Sub-sample Analyses Based on Size and Book-to-Market

Bivariate-sorted and equal-weighted decile portfolios are formed every month from 1965 to 2009 by sorting stocks based on continuing overreaction for each size and book-to-market quintile. The size-grouped portfolios are defined annually using the NYSE market equity quintiles in June of each year. After partitioning all stocks into five groups based on size or book-to-market, within each group we sort the stocks into deciles using the 12-month CO measure. Panel A represents average monthly returns for 6-month holding periods. The monthly return for a 6-month holding period is the equal-weighted average of returns from strategies implemented in the past 6 months. The numbers in parentheses in Panel A are simple *t*-statistics for monthly returns. Panel B reports the Fama-French three-factor alphas for CO portfolios and the last row presents the alphas of hedge portfolios that are long portfolios 10 and short portfolio 1. The numbers in parentheses in Panel B are White's heteroskedasticity-corrected *t*-statistics.

Panel A: Raw returns

| | Size | | | | | Book-to-Market | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Portfolio | Small | 2 | 3 | 4 | Big | Low | 2 | 3 | 4 | High |
| 1 (Downward) | 0.71 | 0.74 | 0.76 | 0.74 | 0.59 | 0.19 | 0.78 | 0.76 | 0.95 | 1.02 |
| 2 | 1.01 | 0.87 | 0.90 | 0.95 | 0.81 | 0.32 | 0.82 | 0.96 | 1.20 | 1.32 |
| 3 | 1.14 | 1.02 | 1.06 | 0.91 | 0.84 | 0.45 | 0.83 | 1.10 | 1.28 | 1.41 |
| 4 | 1.27 | 1.12 | 1.08 | 1.04 | 0.84 | 0.58 | 0.94 | 1.12 | 1.27 | 1.48 |
| 5 | 1.37 | 1.21 | 1.13 | 1.08 | 0.90 | 0.65 | 0.97 | 1.21 | 1.32 | 1.66 |
| 6 | 1.40 | 1.26 | 1.15 | 1.16 | 0.95 | 0.74 | 1.06 | 1.23 | 1.40 | 1.61 |
| 7 | 1.49 | 1.32 | 1.22 | 1.16 | 0.97 | 0.83 | 1.10 | 1.26 | 1.48 | 1.70 |
| 8 | 1.58 | 1.44 | 1.28 | 1.23 | 1.00 | 0.98 | 1.17 | 1.34 | 1.50 | 1.76 |
| 9 | 1.64 | 1.42 | 1.30 | 1.19 | 1.04 | 1.08 | 1.26 | 1.36 | 1.51 | 1.82 |
| 10 (Upward) | 1.72 | 1.55 | 1.45 | 1.34 | 1.20 | 1.22 | 1.36 | 1.50 | 1.62 | 1.94 |
| 10−1 | 1.00 | 0.81 | 0.68 | 0.60 | 0.61 | 1.04 | 0.58 | 0.74 | 0.67 | 0.92 |
| | (6.17) | (4.41) | (3.70) | (3.05) | (3.25) | (5.27) | (3.15) | (4.22) | (3.85) | (5.57) |

Panel B: Fama-French three-factor alphas

| | Size | | | | | Book-to-Market | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Portfolio | Small | 2 | 3 | 4 | Big | Low | 2 | 3 | 4 | High |
| 1 (Downward) | −0.67 | −0.65 | −0.53 | −0.41 | −0.44 | −0.92 | −0.45 | −0.49 | −0.36 | −0.36 |
| 2 | −0.39 | −0.46 | −0.34 | −0.18 | −0.15 | −0.76 | −0.36 | −0.29 | −0.12 | −0.12 |
| 3 | −0.27 | −0.29 | −0.16 | −0.21 | −0.11 | −0.59 | −0.32 | −0.14 | −0.03 | −0.02 |
| 4 | −0.11 | −0.18 | −0.11 | −0.07 | −0.06 | −0.44 | −0.21 | −0.09 | −0.01 | 0.06 |
| 5 | 0.00 | −0.08 | −0.04 | 0.00 | −0.01 | −0.34 | −0.16 | 0.00 | 0.05 | 0.23 |
| 6 | 0.06 | 0.00 | 0.01 | 0.09 | 0.04 | −0.23 | −0.07 | 0.03 | 0.15 | 0.21 |
| 7 | 0.16 | 0.09 | 0.09 | 0.09 | 0.08 | −0.13 | −0.01 | 0.07 | 0.23 | 0.30 |
| 8 | 0.27 | 0.22 | 0.17 | 0.21 | 0.11 | 0.05 | 0.10 | 0.18 | 0.27 | 0.40 |
| 9 | 0.38 | 0.22 | 0.22 | 0.18 | 0.16 | 0.16 | 0.20 | 0.21 | 0.30 | 0.50 |
| 10 (Upward) | 0.50 | 0.43 | 0.42 | 0.41 | 0.39 | 0.31 | 0.37 | 0.43 | 0.48 | 0.68 |
| 10−1 | 1.17 | 1.07 | 0.94 | 0.82 | 0.83 | 1.23 | 0.81 | 0.92 | 0.84 | 1.04 |
| | (7.61) | (6.21) | (5.15) | (3.96) | (4.33) | (6.39) | (4.68) | (5.37) | (4.83) | (6.54) |

# Table 5. Benchmark-Adjusted Returns of Portfolios Based on Continuing Overreaction and Momentum

Panel A reports benchmark-adjusted monthly returns for the CO and momentum portfolios using data on NYSE/AMEX/NASDAQ stocks for the period 1965-2009. The monthly return is the equal-weighted average of returns from strategies implemented in the past 6 months. The benchmark adjustment is based on equal-weighted decile portfolios. The benchmark-adjusted returns are computed by subtracting the monthly returns of the appropriate benchmark portfolio from the individual stock's monthly returns. The numbers in parentheses are simple *t*-statistics for monthly returns. In Panel B, we restrict our sample to the years from 1980 to 2009.

Panel A: 1965-2009

| CO Portfolio | Unadjusted Returns | Momentum-Adjusted Returns | Momentum Portfolio | Unadjusted Returns | CO-Adjusted Returns |
|---|---|---|---|---|---|
| 1 (Downward) | 0.60 (2.24) | −0.22 (−4.73) | 1 (Loser) | 0.49 (1.23) | −0.36 (−2.14) |
| 2 | 0.84 (3.08) | −0.08 (−3.28) | 2 | 0.93 (3.03) | −0.01 (−0.14) |
| 3 | 0.96 (3.58) | −0.05 (−2.46) | 3 | 1.02 (3.81) | 0.01 (0.35) |
| 4 | 1.04 (4.00) | −0.04 (−2.11) | 4 | 1.11 (4.58) | 0.05 (1.12) |
| 5 | 1.15 (4.44) | 0.00 (0.07) | 5 | 1.17 (5.19) | 0.05 (0.97) |
| 6 | 1.21 (4.75) | 0.01 (0.57) | 6 | 1.24 (5.72) | 0.06 (1.02) |
| 7 | 1.28 (5.13) | 0.03 (1.41) | 7 | 1.30 (5.94) | 0.05 (0.95) |
| 8 | 1.37 (5.51) | 0.06 (3.16) | 8 | 1.36 (6.03) | 0.06 (1.12) |
| 9 | 1.46 (5.85) | 0.11 (4.88) | 9 | 1.43 (5.64) | 0.07 (1.34) |
| 10 (Upward) | 1.59 (5.85) | 0.18 (5.24) | 10 (Winner) | 1.44 (4.59) | 0.02 (0.17) |
| 10−1 | 0.99 (6.09) | 0.41 (6.29) | 10−1 | 0.95 (3.66) | 0.37 (2.03) |

Panel B: 1980-2009

| CO Portfolio | Unadjusted Returns | Momentum-Adjusted Returns | Momentum Portfolio | Unadjusted Returns | CO-Adjusted Returns |
|---|---|---|---|---|---|
| 1 (Downward) | 0.48 (1.55) | −0.24 (−4.16) | 1 (Loser) | 0.34 (0.69) | −0.44 (−2.00) |
| 2 | 0.77 (2.45) | −0.08 (−2.61) | 2 | 0.87 (2.44) | 0.00 (−0.05) |
| 3 | 0.92 (2.98) | −0.04 (−1.83) | 3 | 0.98 (3.25) | 0.04 (0.79) |
| 4 | 1.00 (3.35) | −0.05 (−1.99) | 4 | 1.09 (4.09) | 0.08 (1.57) |
| 5 | 1.11 (3.78) | −0.01 (−0.32) | 5 | 1.17 (4.74) | 0.09 (1.31) |
| 6 | 1.17 (4.09) | 0.00 (−0.12) | 6 | 1.26 (5.30) | 0.11 (1.48) |
| 7 | 1.25 (4.48) | 0.02 (0.89) | 7 | 1.30 (5.45) | 0.09 (1.28) |
| 8 | 1.35 (4.82) | 0.07 (2.94) | 8 | 1.36 (5.42) | 0.09 (1.33) |
| 9 | 1.43 (5.10) | 0.12 (4.49) | 9 | 1.37 (4.70) | 0.04 (0.64) |
| 10 (Upward) | 1.56 (4.93) | 0.22 (4.79) | 10 (Winner) | 1.31 (3.44) | −0.09 (−0.76) |
| 10−1 | 1.07 (5.31) | 0.46 (5.83) | 10−1 | 0.97 (2.97) | 0.35 (1.51) |

# Table 6.
# Returns of Portfolios Double-Sorted on Continuing Overreaction and Momentum

Bivariate-sorted decile portfolios are formed every month from 1965 to 2009 by sorting stocks based on continuing overreaction (momentum) after controlling for momentum (continuing overreaction). After partitioning all stocks into five groups based on momentum (continuing overreaction), within each group we sort the stocks into deciles using the 12-month CO measure (MOM). This table represents average monthly returns for a 6-month holding period. The monthly return for a 6-month holding period consists of monthly returns from strategies implemented in the past 6 months and the corresponding simple *t*-statistics are reported in parentheses.

Panel A: First sort on momentum

| | Equal-Weighted | | | | | Value-Weighted | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Portfolio | Loser | 2 | 3 | 4 | Winner | Loser | 2 | 3 | 4 | Winner |
| 1 (Downward) | 0.31 | 0.82 | 0.99 | 0.99 | 1.05 | 0.12 | 0.57 | 0.72 | 0.81 | 0.96 |
| 2 | 0.50 | 0.97 | 1.12 | 1.19 | 1.16 | 0.41 | 0.79 | 0.88 | 0.87 | 0.96 |
| 3 | 0.60 | 0.99 | 1.11 | 1.25 | 1.32 | 0.41 | 0.77 | 0.84 | 0.94 | 1.19 |
| 4 | 0.69 | 1.02 | 1.18 | 1.32 | 1.38 | 0.43 | 0.73 | 0.93 | 0.97 | 1.25 |
| 5 | 0.69 | 1.06 | 1.21 | 1.36 | 1.45 | 0.54 | 0.76 | 0.77 | 1.01 | 1.28 |
| 6 | 0.76 | 1.13 | 1.25 | 1.36 | 1.49 | 0.63 | 0.72 | 0.85 | 1.02 | 1.26 |
| 7 | 0.91 | 1.12 | 1.26 | 1.41 | 1.55 | 0.64 | 0.88 | 0.87 | 1.00 | 1.38 |
| 8 | 0.87 | 1.12 | 1.26 | 1.45 | 1.62 | 0.58 | 0.85 | 0.84 | 1.10 | 1.34 |
| 9 | 0.85 | 1.16 | 1.34 | 1.49 | 1.68 | 0.61 | 0.89 | 0.95 | 1.12 | 1.42 |
| 10 (Upward) | 0.92 | 1.21 | 1.35 | 1.50 | 1.64 | 0.64 | 1.00 | 1.06 | 1.20 | 1.64 |
| 10−1 | 0.61 | 0.39 | 0.36 | 0.51 | 0.59 | 0.52 | 0.44 | 0.34 | 0.40 | 0.68 |
| | (4.01) | (3.23) | (3.89) | (5.45) | (5.00) | (2.82) | (3.10) | (2.99) | (3.22) | (3.91) |

Panel B: First sort on continuing overreaction

| Portfolio | Downward CO | 2 | 3 | 4 | Upward CO | Downward CO | 2 | 3 | 4 | Upward CO |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 (Loser) | −0.02 | 0.56 | 0.88 | 1.11 | 1.24 | −0.09 | 0.35 | 0.56 | 0.94 | 1.10 |
| 2 | 0.52 | 0.88 | 1.12 | 1.24 | 1.41 | 0.16 | 0.56 | 0.73 | 0.97 | 1.14 |
| 3 | 0.60 | 1.01 | 1.12 | 1.27 | 1.49 | 0.27 | 0.69 | 0.83 | 0.88 | 1.08 |
| 4 | 0.70 | 1.00 | 1.20 | 1.32 | 1.54 | 0.48 | 0.71 | 0.80 | 0.90 | 1.21 |
| 5 | 0.85 | 1.04 | 1.22 | 1.37 | 1.54 | 0.56 | 0.74 | 0.74 | 0.95 | 1.14 |
| 6 | 0.85 | 1.06 | 1.24 | 1.37 | 1.54 | 0.55 | 0.80 | 0.90 | 0.97 | 1.26 |
| 7 | 0.91 | 1.11 | 1.23 | 1.39 | 1.66 | 0.61 | 0.86 | 0.90 | 1.04 | 1.32 |
| 8 | 0.94 | 1.13 | 1.30 | 1.45 | 1.65 | 0.65 | 0.87 | 1.05 | 1.18 | 1.43 |
| 9 | 0.98 | 1.13 | 1.31 | 1.43 | 1.65 | 0.76 | 0.85 | 0.96 | 1.22 | 1.63 |
| 10 (Winner) | 0.87 | 1.11 | 1.17 | 1.31 | 1.50 | 0.65 | 0.94 | 0.98 | 1.32 | 1.75 |
| 10−1 | 0.89 | 0.55 | 0.29 | 0.20 | 0.26 | 0.74 | 0.59 | 0.42 | 0.38 | 0.66 |
| | (2.85) | (2.06) | (1.21) | (0.95) | (1.18) | (1.99) | (1.84) | (1.43) | (1.47) | (2.26) |

## Table 7. Cross-Sectional Return Regressions

For each month from January 1965 to June 2009 we run a firm-level cross-sectional regression of the 6-month holding period return (in percentages) on continuing overreaction (CO), momentum variable (MOM), and other control variables defined in the Appendix B. CO and momentum variable are calculated over the past 12 months. Each column reports the time-series averages of the cross-sectional regression slope coefficients and adjusted $R^2$. The *t*-statistics are Newey-West (1987) adjusted with six lags and reported in parentheses. *, **, and *** represents significance at the 10%, 5%, and 1% level, respectively.

| Model | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| CO | 0.060*** | | 0.048*** | 0.028*** |
| | (6.12) | | (6.94) | (5.04) |
| MOM | | 0.028*** | 0.013 | 0.008 |
| | | (2.83) | (1.34) | (1.07) |
| BETA | | | | 0.318* |
| | | | | (1.90) |
| SIZE | | | | −0.685*** |
| | | | | (−3.34) |
| BM | | | | 1.618*** |
| | | | | (4.64) |
| REV | | | | −0.006 |
| | | | | (−0.58) |
| ILLIQ | | | | 0.012*** |
| | | | | (2.62) |
| IVOL | | | | −0.512*** |
| | | | | (−2.79) |
| TURN | | | | −1.613*** |
| | | | | (−3.11) |
| UCG | | | | 2.555*** |
| | | | | (4.04) |
| Adj. $R^2$ | 0.009 | 0.013 | 0.017 | 0.079 |

# Table 8. Returns of Portfolios Double-Sorted on Continuing Overreaction and Alternative Explanations

Bivariate-sorted decile portfolios are formed every month from 1965 to 2009 by sorting stocks based on continuing overreaction after controlling for the difference in the number of positive and negative return months (Npos_neg) or information discreteness (PosID/NegID). In Panel A (B), we partition all stocks into five (six) groups based on Npos_neg (PosID and NegID), and within each group we sort the stocks into quintiles using the 12-month CO measure. In Panel B, we exclude stocks with zero 12-month past returns (MOM = 0) by the definition of PosID and NegID. This table represents average monthly returns for a 6-month holding period. The monthly return for a 6-month holding period consists of monthly returns from strategies implemented in the past 6 months. The corresponding simple *t*-statistics are reported in parentheses.

Panel A: First sort on Npos_neg

| | Equal-Weighted | | | | | Value-Weighted | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Portfolio | Npos_neg = 1 | 2 | 3 | 4 | Npos_neg = 5 | Npos_neg = 1 | 2 | 3 | 4 | Npos_neg = 5 |
| CO = 1 | 0.44 | 0.79 | 0.93 | 1.06 | 1.25 | 0.36 | 0.64 | 0.75 | 0.84 | 0.99 |
| 2 | 0.68 | 0.99 | 1.12 | 1.19 | 1.33 | 0.57 | 0.73 | 0.87 | 0.87 | 1.00 |
| 3 | 0.75 | 1.05 | 1.19 | 1.31 | 1.41 | 0.61 | 0.71 | 0.85 | 0.94 | 1.03 |
| 4 | 0.86 | 1.17 | 1.30 | 1.41 | 1.54 | 0.64 | 0.81 | 0.95 | 1.05 | 1.22 |
| CO = 5 | 0.94 | 1.23 | 1.42 | 1.54 | 1.71 | 0.71 | 0.96 | 1.15 | 1.21 | 1.41 |
| 5−1 | 0.50 | 0.44 | 0.49 | 0.48 | 0.46 | 0.35 | 0.32 | 0.40 | 0.37 | 0.42 |
| | (4.19) | (3.47) | (4.00) | (4.25) | (4.24) | (2.28) | (2.22) | (3.02) | (2.82) | (2.94) |

Panel B: First sort on PosID and NegID

| | Equal-Weighted | | | | | | Value-Weighted | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | MOM < 0 | | | MOM > 0 | | | MOM < 0 | | | MOM > 0 | | |
| Portfolio | NegID = 3 | 2 | NegID = 1 | PosID = 1 | 2 | PosID = 3 | NegID = 3 | 2 | NegID = 1 | PosID = 1 | 2 | PosID = 3 |
| CO = 1 | 0.14 | 0.60 | 0.85 | 0.94 | 1.09 | 1.13 | 0.20 | 0.43 | 0.43 | 0.70 | 0.83 | 0.82 |
| 2 | 0.36 | 0.83 | 0.94 | 1.10 | 1.24 | 1.26 | 0.43 | 0.57 | 0.63 | 0.77 | 0.80 | 0.94 |
| 3 | 0.47 | 0.91 | 1.04 | 1.14 | 1.34 | 1.38 | 0.42 | 0.58 | 0.64 | 0.80 | 0.86 | 1.03 |
| 4 | 0.54 | 0.95 | 1.12 | 1.23 | 1.49 | 1.45 | 0.50 | 0.81 | 0.65 | 0.99 | 1.05 | 1.11 |
| CO = 5 | 0.59 | 1.03 | 1.21 | 1.31 | 1.63 | 1.69 | 0.60 | 0.69 | 0.71 | 1.18 | 1.26 | 1.41 |
| 5−1 | 0.46 | 0.42 | 0.36 | 0.38 | 0.55 | 0.56 | 0.40 | 0.27 | 0.28 | 0.49 | 0.43 | 0.60 |
| | (3.64) | (4.38) | (4.16) | (3.11) | (4.69) | (4.75) | (2.66) | (2.29) | (2.56) | (3.49) | (3.03) | (3.98) |

# Table 9. Cross-Sectional Return Regressions with Return Consistency and Information Discreteness

For each month from January 1965 to June 2009 we run a firm-level cross-sectional regression of the 6-month holding period return (in percentages) on continuing overreaction (CO), momentum variable (MOM), information discreteness (PosID/NegID), return consistency (PosRC/NegRC), the difference in the number of positive and negative return months (Npos_neg), and other control variables defined in Appendix B. CO and the momentum variable are calculated over the past 12 months. Each column reports the time-series averages of the cross-sectional regression slope coefficients and adjusted $R^2$. The *t*-statistics are Newey-West (1987) adjusted with six lags and reported in parentheses. *, **, and *** represents significance at the 10%, 5%, and 1% level, respectively.

| Model | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| CO | 0.041*** | 0.045*** | 0.025*** | 0.025*** | 0.026*** |
| | (5.57) | (5.10) | (4.40) | (4.32) | (4.00) |
| MOM | 0.003 | 0.012 | 0.002 | 0.007 | 0.003 |
| | (0.32) | (1.25) | (0.31) | (0.97) | (0.35) |
| PosID | 0.094 | | 0.097*** | | 0.101*** |
| | (1.59) | | (2.87) | | (3.22) |
| NegID | −0.317*** | | −0.191*** | | −0.177*** |
| | (−4.54) | | (−5.30) | | (−5.23) |
| PosRC | | −0.120 | | 0.297 | 0.050 |
| | | (−0.23) | | (1.03) | (0.25) |
| NegRC | | −1.734*** | | −0.926*** | −0.464* |
| | | (−3.50) | | (−3.66) | (−1.95) |
| Npos_neg | | | | | −0.019 |
| | | | | | (−0.37) |
| BETA | | | 0.342** | 0.317* | 0.333** |
| | | | (2.11) | (1.91) | (2.09) |
| SIZE | | | −0.756*** | −0.695*** | −0.751*** |
| | | | (−3.77) | (−3.43) | (−3.78) |
| BM | | | 1.545*** | 1.597*** | 1.528*** |
| | | | (4.45) | (4.60) | (4.42) |
| REV | | | −0.006 | −0.006 | −0.005 |
| | | | (−0.53) | (−0.53) | (−0.50) |
| ILLIQ | | | 0.011** | 0.011** | 0.011** |
| | | | (2.48) | (2.60) | (2.49) |
| IVOL | | | −0.489*** | −0.507*** | −0.493*** |
| | | | (−2.79) | (−2.82) | (−2.88) |
| TURN | | | −1.454*** | −1.602*** | −1.464*** |
| | | | (−2.96) | (−3.12) | (−3.03) |
| UCG | | | 2.297*** | 2.441*** | 2.254*** |
| | | | (3.50) | (3.85) | (3.42) |
| Adj. $R^2$ | 0.029 | 0.021 | 0.082 | 0.080 | 0.083 |

# Table 10.
# Returns of Portfolios Based on an Alternative Measure of Continuing Overreaction

This table reports the equal-weighted (EW) and value-weighted (VW) average monthly returns for a 6-month holding period ($K$ = 6) based on the 12-month continuing overreaction measure constructed from idiosyncratic volatility (IVOL) instead of trading volume ($CO_{IVOL}$). Portfolio 1 (10) comprises stocks with the lowest (highest) values in $CO_{IVOL}$. The benchmark portfolios are formed on the portfolio formation date using all NYSE/AMEX/NASDAQ firms available at the time of portfolio formation. The benchmark-adjusted returns are computed by subtracting the equal-weighted or value-weighted monthly returns of the appropriate benchmark portfolio from the individual stock's monthly returns. The numbers in parentheses are simple $t$-statistics for monthly returns.

| | Raw Returns | | Three-Factor Alphas | | Size- and Book-to-Market-Adjusted Returns | | Momentum-Adjusted Returns | |
|---|---|---|---|---|---|---|---|---|
| $CO_{IVOL}$ Portfolio | EW | VW | EW | VW | EW | VW | EW | VW |
| 1 (Downward) | 0.52 | 0.48 | −0.82 | −0.53 | −0.45 | −0.31 | −0.26 | −0.16 |
| | (1.70) | (1.91) | (−5.58) | (−3.88) | (−5.66) | (−3.07) | (−7.37) | (−2.98) |
| 2 | 0.85 | 0.73 | −0.44 | −0.21 | −0.21 | −0.12 | −0.08 | −0.01 |
| | (3.04) | (3.24) | (−4.00) | (−2.05) | (−4.30) | (−1.62) | (−3.78) | (−0.19) |
| 3 | 0.98 | 0.71 | −0.30 | −0.21 | −0.13 | −0.14 | −0.04 | −0.04 |
| | (3.62) | (3.34) | (−3.18) | (−2.81) | (−3.64) | (−2.72) | (−2.07) | (−1.45) |
| 4 | 1.07 | 0.77 | −0.18 | −0.13 | −0.06 | −0.09 | −0.02 | −0.02 |
| | (4.08) | (3.72) | (−2.26) | (−2.05) | (−2.60) | (−2.02) | (−0.89) | (−0.54) |
| 5 | 1.14 | 0.82 | −0.10 | −0.08 | −0.03 | −0.05 | −0.01 | −0.02 |
| | (4.42) | (4.05) | (−1.47) | (−1.54) | (−1.47) | (−1.46) | (−0.64) | (−0.80) |
| 6 | 1.23 | 0.85 | 0.02 | −0.02 | 0.05 | −0.04 | 0.02 | −0.01 |
| | (4.86) | (4.22) | (0.30) | (−0.42) | (2.99) | (−1.37) | (1.35) | (−0.38) |
| 7 | 1.29 | 0.89 | 0.10 | 0.03 | 0.09 | −0.01 | 0.04 | −0.01 |
| | (5.22) | (4.53) | (2.00) | (0.72) | (3.72) | (−0.50) | (2.25) | (−0.24) |
| 8 | 1.36 | 0.92 | 0.21 | 0.05 | 0.15 | 0.02 | 0.07 | 0.00 |
| | (5.59) | (4.63) | (4.47) | (1.23) | (4.47) | (0.45) | (4.00) | (0.01) |
| 9 | 1.45 | 1.04 | 0.32 | 0.20 | 0.22 | 0.12 | 0.11 | 0.05 |
| | (6.05) | (5.25) | (6.81) | (3.96) | (4.67) | (2.33) | (4.43) | (1.66) |
| 10 (Upward) | 1.58 | 1.21 | 0.52 | 0.39 | 0.33 | 0.22 | 0.18 | 0.12 |
| | (6.63) | (5.83) | (7.52) | (4.82) | (4.09) | (2.71) | (4.14) | (2.74) |
| 10−1 | 1.06 | 0.73 | 1.34 | 0.92 | 0.77 | 0.53 | 0.44 | 0.27 |
| | (5.63) | (3.76) | (7.19) | (4.62) | (5.11) | (3.19) | (7.89) | (3.72) |

## Table 11. Cross-Sectional Return Regressions with an Alternative Measure of Continuing Overreaction

For each month from January 1965 to June 2009 we run a firm-level cross-sectional regression of the 6-month holding period return (in percentages) on the alternative continuing overreaction calculated using idiosyncratic volatility ($CO_{IVOL}$), momentum variable (MOM), information discreteness (PosID/NegID), return consistency (PosRC/NegRC), the difference in the number of positive and negative return months (Npos_neg), and other control variables defined in Appendix B. Each column reports the time-series averages of the cross-sectional regression slope coefficients and adjusted $R^2$. The *t*-statistics are Newey-West (1987) adjusted with six lags and reported in parentheses. *, **, and *** represents significance at the 10%, 5%, and 1% level, respectively.

| Model | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| $CO_{IVOL}$ | 0.073***<br>(6.84) | 0.060***<br>(8.40) | 0.038***<br>(6.01) | 0.035***<br>(5.49) | 0.037***<br>(5.22) | 0.048***<br>(5.29) |
| MOM | | 0.013<br>(1.42) | 0.007<br>(1.06) | 0.002<br>(0.26) | 0.007<br>(1.03) | 0.003<br>(0.43) |
| PosID | | | | 0.095***<br>(2.83) | | 0.114***<br>(3.73) |
| NegID | | | | −0.184***<br>(−5.17) | | −0.191***<br>(−5.63) |
| PosRC | | | | | 0.045<br>(0.14) | 0.106<br>(0.51) |
| NegRC | | | | | −0.578**<br>(−2.18) | −0.392*<br>(−1.66) |
| Npos_neg | | | | | | −0.156**<br>(−2.44) |
| BETA | | | 0.328*<br>(1.95) | 0.350**<br>(2.15) | 0.321*<br>(1.93) | 0.333**<br>(2.09) |
| SIZE | | | −0.735***<br>(−3.53) | −0.802***<br>(−3.94) | −0.731***<br>(−3.55) | −0.776***<br>(−3.85) |
| BM | | | 1.598***<br>(4.60) | 1.528***<br>(4.42) | 1.575***<br>(4.56) | 1.494***<br>(4.35) |
| REV | | | −0.005<br>(−0.50) | −0.005<br>(−0.45) | −0.005<br>(−0.45) | −0.004<br>(−0.39) |
| ILLIQ | | | 0.011**<br>(2.61) | 0.011**<br>(2.48) | 0.011**<br>(2.60) | 0.011**<br>(2.48) |
| IVOL | | | −0.475***<br>(−2.56) | −0.456**<br>(−2.56) | −0.477***<br>(−2.61) | −0.467***<br>(−2.67) |
| TURN | | | −1.547***<br>(−2.97) | −1.402***<br>(−2.83) | −1.548***<br>(−2.99) | −1.377***<br>(−2.83) |
| UCG | | | 2.461***<br>(3.89) | 2.216***<br>(3.37) | 2.376***<br>(3.73) | 2.180***<br>(3.31) |
| Adj. $R^2$ | 0.010 | 0.018 | 0.079 | 0.082 | 0.080 | 0.083 |

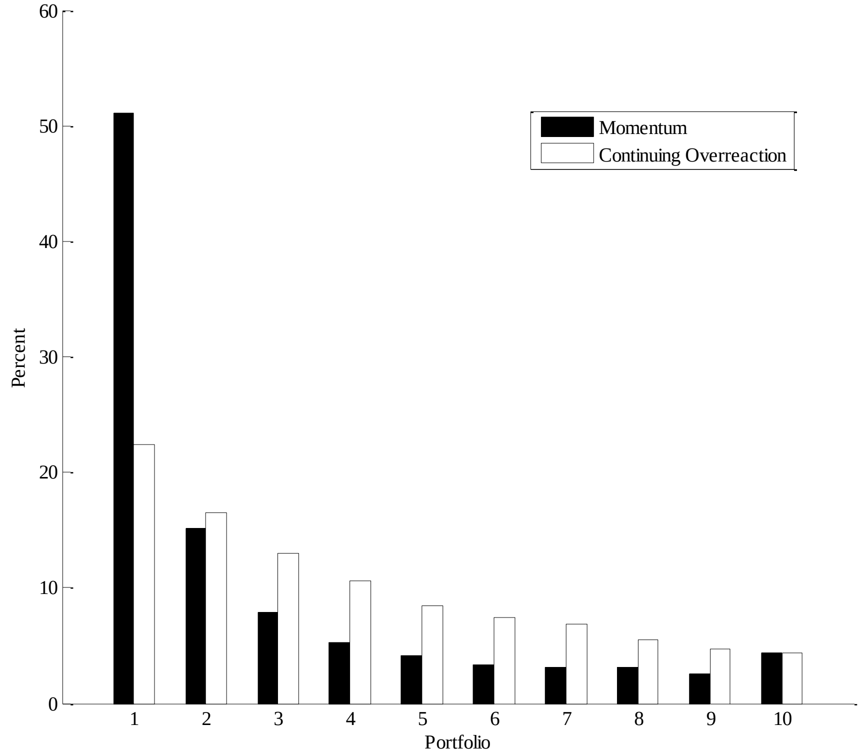


**Figure 1. The proportions of poor performance delistings in each portfolio to total poor performance delistings.** This chart reports the proportions of delisted firms due to poor performance in each CO and momentum portfolio to entire delistings due to poor performance. We define the poor performance delistings as issues that have a CRSP delist code of 552, 560, 561, 574, 580, 582, and 584. The solid bars represent momentum portfolios, and the open bars represent the CO portfolios.

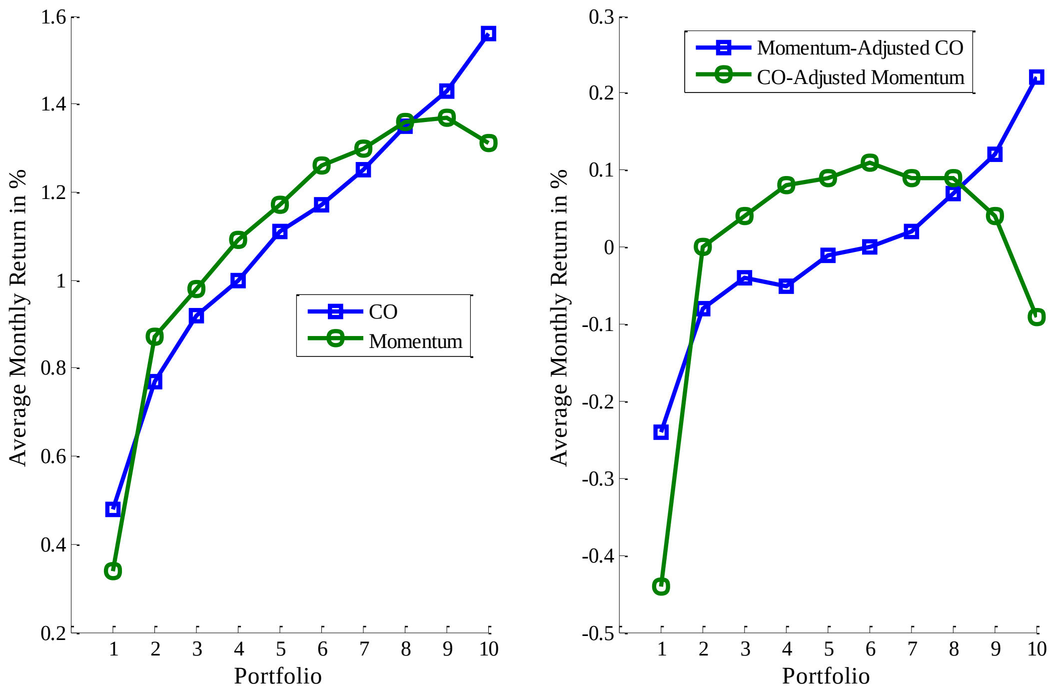


**Figure 2. Comparison of strategies based on investor continuing overreaction and momentum.** The left graph represents average monthly returns for the continuing overreaction and momentum strategies involving NYSE/AMEX/NASDAQ stocks for 1980–2009. At the beginning of each month, all stocks are sorted by the CO measure and the momentum variable over the previous 12 months, respectively. Each stock is assigned to one of ten portfolios and held for 6 months. The right graph depicts benchmark-adjusted returns for the continuing overreaction and momentum strategies using each other's strategy as a benchmark. The benchmark-adjusted return is computed by subtracting the monthly return of the benchmark portfolio from the individual stock's monthly return.

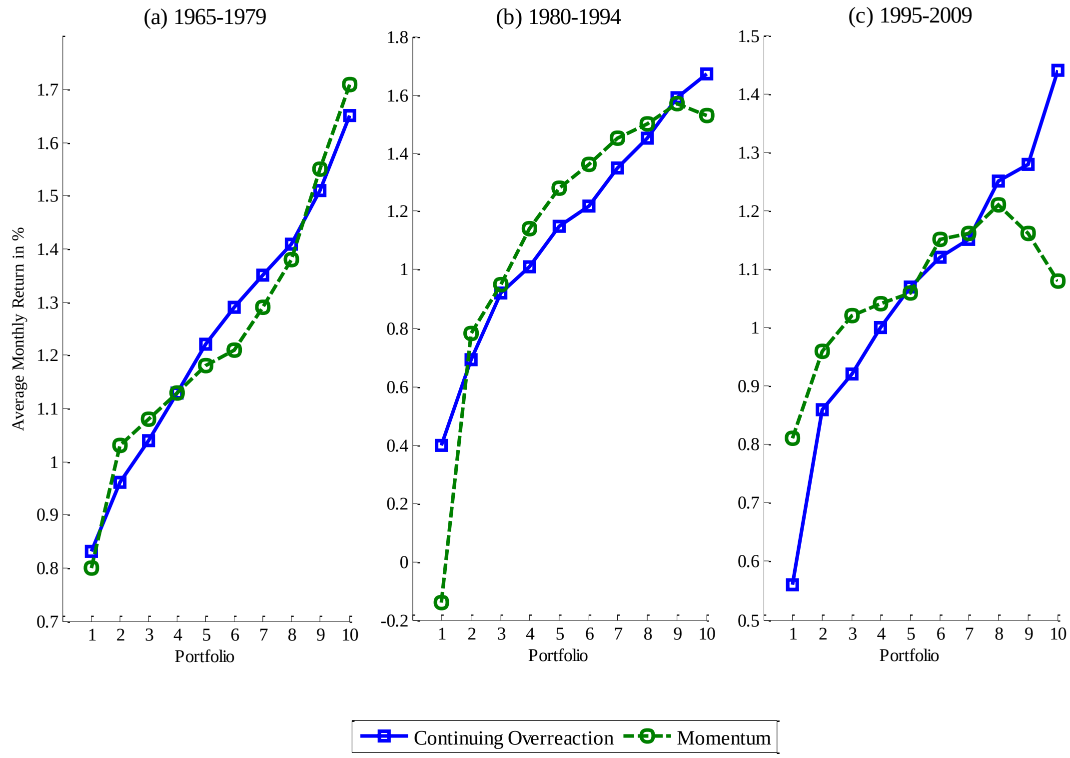


**Figure 3. Sub-period analysis for the continuing overreaction and momentum strategies.** For sub-period analysis, our 45-year sample period is divided into three periods of 15 years (i.e., 1965‑1979, 1980–1994, and 1995–2009). Each graph presents average monthly returns from strategies based on the CO measure and the momentum variable calculated over the past 12 months. Each portfolio is held for 6 months.

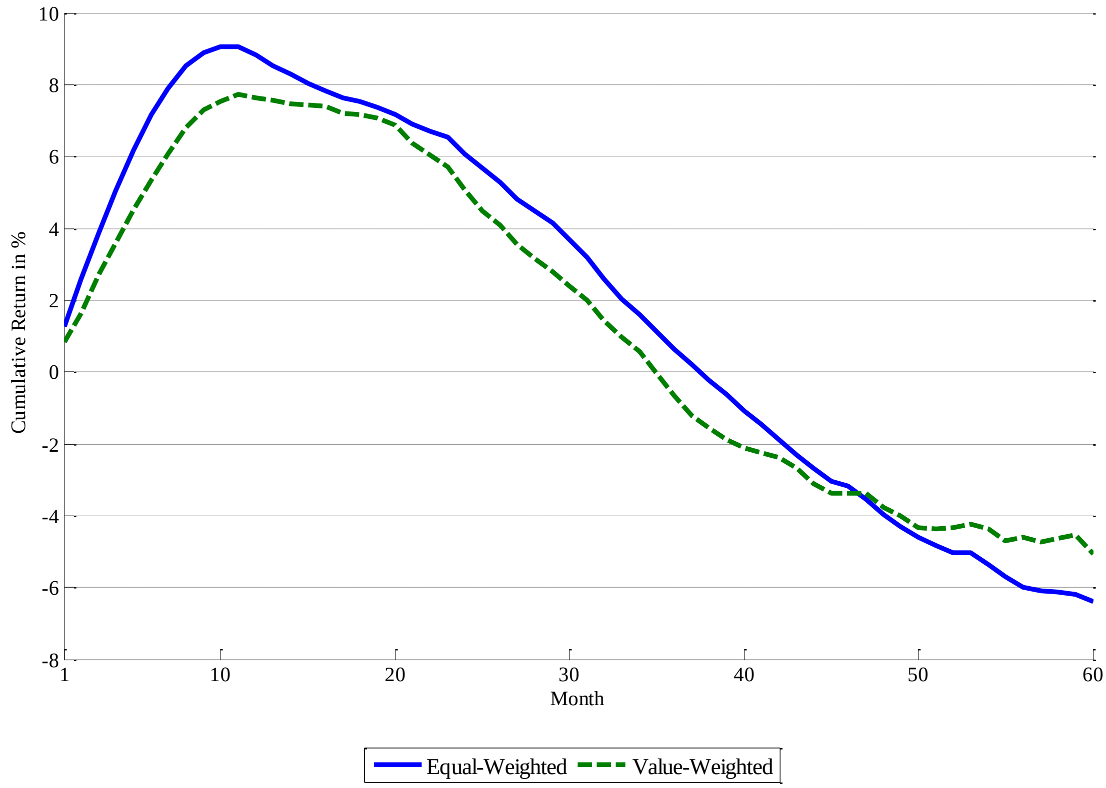


**Figure 4. Cumulative returns of zero-investment portfolios based on the 12-month CO measure.** This graph depicts cumulative returns of zero-investment portfolios for the next 60 months after the portfolio formation. At the beginning of each month, stocks are sorted based on the CO measure calculated using signed volumes over the previous 12 months ($J$ = 12) and divided into ten portfolios. The zero-investment portfolios buy top CO deciles and sell bottom CO deciles.