Short-term overreaction and the cross-section of stock returns

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Abstract

Our study introduces a measure of Short-Term Overreaction (STO) based on weighted daily signed volume as a predictor of stock returns. We find that STO predicts subsequent stock returns independently of the well-known short-term return reversal and even subsumes the predictive power of the short-term return reversal. It is also a significant negative predictor of abnormal returns around subsequent earnings announcements, suggesting that investors are overly optimistic (pessimistic) about high (low) STO stocks. The return predictability of STO tends to be stronger when investor sentiment is high and for small and illiquid stocks. Our findings provide insights into the dynamics of investor overreaction in financial markets.

JEL classification: G11; G12; G14

Keywords: Overreaction, Signed volume, Short-term return reversal

1. Introduction

A well-known finding in the asset pricing literature is that stock returns exhibit reversal at short horizons such as one month. For example, Jegadeesh (1990) shows that a reversal strategy of buying (selling) stocks with low (high) returns over the past month and holding them for one month yields significant profit. Some studies suggest that investor overreaction followed by subsequent correction leads to short-term return reversal (e.g., Cooper 1999, Subrahmanyam 2005). Others suggest that price reversal serves as a compensation for liquidity providers who accommodate the price pressures caused by non-informational trades (e.g., Campbell et al. 1993, Avramov et al. 2006).

Both strands of the literature suggest that unusual trading activities, whether they are driven by investor overreaction or by non-informational trades, are the underlying driver of short-term return predictability. Prior studies have used trading volume as a proxy of investor overreaction (e.g., Odean 1998, Byun et al. 2016), and Campbell et al. (1993) argue that selling pressure by non-informational traders must reveal itself in unusual volume. If so, a direct measure of overreaction based on trading volume can be a better predictor of short-term return than past return.

Motivated by this idea, we propose a noble predictor of short-term return based on weighted daily signed volume. We multiply the daily trading volume by the sign of the contemporaneous return to capture both the magnitude and direction of investor overreaction.[1] Then we assign higher weights to the daily signed volumes of later dates to identify the trend of overreaction. The monthly weighted signed volume is computed as the sum of the daily weighted signed volumes divided by the average trading volume during the month.

[1] While trading volume can also capture non-information driven trades, we provide evidence that the return predictability of our measure is likely to due to investor overreaction rather than the compensation for liquidity providers in Section 3.4.

We find that our measure of short-term overreaction (STO) defined as the abnormal level of weighted signed trading volume predicts stock returns in the subsequent month. Stocks in the lowest decile of STO outperform those in the highest STO decile in the subsequent month by 0.77% (0.90%) in equal-weighted (value-weighted) portfolio returns. The results are similar when we examine risk-adjusted returns (alphas). For example, the lowest STO decile outperforms the highest STO decile by 0.73% (1.00%) in Fama-French 5-factor alphas of equal-weighted (value-weighted) portfolios. The results suggest that an upward (downward) overreaction predicts negative (positive) future returns.

As our measure is motivated as an underlying driver of short-term return reversal, we ensure that our results are not subsumed by the return predictability of the past one-month return. The results from double-sort analyses show that the return predictability of the past one-month return largely disappears after controlling for STO, while the return predictability of STO remains significant after controlling for the past one-month return. The results confirm that the return predictability of STO is not subsumed by short-term return reversal. Furthermore, the fact that short-term return reversal largely disappears after controlling for STO suggests that our measure is likely to be a more direct measure of investor short-term overreaction that drives short-term return reversal.

Next, we perform Fama and Macbeth (1973) cross-sectional regressions of monthly stock returns on STO and well-known determinants of cross-sectional returns including past one-month returns. The results show that STO remains to be a strong negative predictor of cross-sectional returns after controlling for the effects of well-known control variables, as well as the effect of short-term return reversal.

While trading volume can capture both the extent of investor overreaction and uninformed trades, one important implication of investor overreaction that differs from that of uninformed trades is how it relates to stock price reactions to public information. If our measure is related to investor overreaction, a positive (negative) STO indicates investors are overly optimistic (pessimistic) about the stock and they will be on average negatively (positively) surprised by subsequent earnings announcements. This predicts that STO is a negative predictor of abnormal returns around subsequent earnings announcements. On the other hand, if the return predictability of STO is the compensation for liquidity providers that absorb uninformed trades, there is no reason why the effect of STO on future returns should be concentrated around public announcements such as earnings announcements. Thus, the liquidity provision story predicts that the relation between STO and subsequent earnings announcement abnormal returns should not differ from the relation between STO and abnormal returns of any future date.

We find that STO is a significant negative predictor of 3-day abnormal returns around subsequent earnings announcements, while STO is not significantly related to 3-day abnormal returns around non-earnings announcement dates. The results support our overreaction story that STO captures short-term overreaction, and that the return predictability of STO is driven by the subsequent correction of short-term overreaction.

In our subsample analysis, we investigate the profitability of the STO strategy across different investor sentiment states and firm characteristics. We divide the sample into high and low sentiment states and find that the STO strategy is more profitable after periods of high investor sentiment. The result is consistent with prior evidence of greater mispricing when investor sentiment is high (e.g., Stambaugh et al., 2012). Classifying stocks based on firm characteristics reveals that the STO strategy performs best among small and illiquid firms.

Our study contributes to the literature on stock return predictability that is likely to be driven by investor overreaction. One of the most well-known anomalies that has been associated with investor overreaction is short-term return reversal. Most prior studies attempt to identify possible causes of short-term return reversal by identifying conditions under which there is stronger short-term return reversal (e.g., Avramov et al. 2006, Conrad et al. 1994, Cooper 1999, Da et al. 2014). In contrast, we take a different approach by constructing a direct measure of investor overreaction, which should be a stronger return predictor than past returns if short-term return reversal is driven by investor overreaction. We show that our measure of investor short-term overreaction, STO, is a strong predictor of future returns and subsumes the effect of past returns, providing support for the investor overreaction explanation of short-term return reversal. Furthermore, we distinguish the investor overreaction explanation of short-term return reversal from the liquidity provision explanation by relating STO to the abnormal returns around subsequent earnings announcements. We find that STO is a negative predictor of abnormal returns around subsequent earnings announcements, suggesting that STO is likely to capture investor overreaction rather than liquidity demand. Overall, our study provides insights into the role of investor overreaction in return predictability, and it may have broader implications for other anomalies that are related to investor overreaction such as the accruals anomaly (e.g., Sloan 1996), the asset growth anomaly (e.g., Cooper et al. 2008), and the long-term reversal anomaly (e.g., DeBondt and Thaler 1995).

The remainder of the paper is organized as follows. In Section 2, we describe our data source and introduce our short-term overreaction variable. In Section 3, we present our main results. In Section 4, we perform the additional analyses and provide the robustness of our results. Section 5 concludes the paper.

2. Data and methodology

2.1. Short-term overreaction measure

Our empirical measure of short-term overreaction is constructed as follows: First, we utilize trading volume as a proxy for the level of investor overreaction (e.g., Odean 1998, Byun et al. 2016). Secondly, we use the sign of contemporaneous returns to identify the direction of overreaction by investors. We construct daily signed volumes based on the assumption that high trading volume accompanied by a positive (negative) return indicates upward (downward) investor overreaction, which predicts a negative (positive) future return. By multiplying the trading volume by the sign of the contemporaneous return, we aim to capture the magnitude and direction of overreaction. The daily signed volume for stock *i* in day *d* is defined as follows:

$$SVOL_{i,d} = \begin{cases} VOL_{i,d} & \text{if } ret_{i,d} > 0 \\ 0 & \text{if } ret_{i,d} = 0 \\ -VOL_{i,d} & \text{if } ret_{i,d} < 0, \end{cases} \tag{1}$$

where $ret_{i,d}$ is the close-to-close daily return and $VOL_{i,d}$ is the trading share volume for each stock i in day d.

Next, we assign increasing weight to daily signed volumes as the date gets closer to the end of the month. The weighted signed volume of stock *i* in month *t* ($WSVOL_{i,t}$) is defined as the sum of daily weighted signed volumes divided by the average daily trading volume during the month:

$$WSVOL_{i,t} = \frac{\sum_{d=1}^{D} SVOL_{i,d} \times W_d}{VOL_{i,t}}, \tag{2}$$

where $SVOL_{i,d}$ is the signed daily volume defined in Equation (1) and *D* is the number of trading days in month *t*. W_d is a weight on the signed volume of trading day *d* of the month, defined as $d/(\sum_{d=1}^{D} d)$ (i.e., $W_d = 2d/D(D+1)$ where $d = 1, 2, \ldots, D$).

Holding the average trading volume constant, the weighted sum will have a higher value when the trading volumes show an increasing trend. Thus, the weighted signed volume helps us identify the trend of overreaction during the month, which can provide information about the phase of the overreaction. For example, a declining trading volume may indicate that the stock is already in the correction phase of overreaction during the formation month, implying that it may not have much predictive power on future returns. In addition, the increasing weighting scheme places a greater emphasis on the overreaction toward the end of the month, which is likely to have a stronger predictive power over subsequent returns.

Our primary variable of interest is the abnormal level of weighted signed volume, which we use as our measure of short-term overreaction ($STO_{i,t}$). To calculate this measure, we subtract $WSVOL_{i,t}$ by the average $WSVOL_{i,t}$ over the previous 12 months. By concentrating on the abnormal level of weighted signed volumes, we aim to uncover short-term deviations from the persistent level of weighted signed volume and assess their potential implications for future price movements. Thus, our measure provides a distinct perspective on the dynamics of investor overreaction in the market.

2.2. Data and Variables

We collect data from multiple databases. The Center for Research in Security Prices (CRSP) database provides monthly and daily stock data, while the Compustat database supplies annual and quarterly accounting data. Institutional ownership information, specifically the 13F filings, is from the Thomson Financial Mutual Funds database. The sample consists of stocks listed on major exchanges, including the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and Nasdaq. Our sample period spans from May 1993 to December 2022. We exclude stocks with a price below $1 per share to eliminate potential market microstructure effects associated with low-priced stocks, and we require a minimum of fifteen daily signed volume observations during month *t* to compute the STO measure.

We construct the well-known firm characteristic variables for the control variables in the firm-level cross-sectional regression. These control variables are short-term return reversal (RET) from Jegadeesh (1990) and Lehmann (1990), bid-ask spread (BAS), market beta (BETA), market capitalization (ME), book-to-market ratio (BM) based on Fama and French (1992), momentum (MOM) from Jegadeesh and Titman (1993), illiquidity (ILLIQ) from Amihud (2002), turnover (TURN), idiosyncratic volatility (IVOL) based on Ang et al. (2006), the maximum daily return in the previous month (MAX) as proposed by Bali et al. (2011), and the stock price (PRC). Further details regarding these variables can be found in the Appendix.

To get a comprehensive understanding of the portfolio's composition sorted by STO, Table 1 provides summary statistics for stocks within each decile. The table presents the monthly averages of mean values across the sample months for various characteristics of stocks in each STO decile. Panel A provides average values of the control variables across STO deciles. Panel B shows the correlation matrix.

[Table 1] about here

3. Empirical analysis

3.1. Portfolio sort analysis

To initiate our analysis, we conduct a univariate sort analysis based on the level of our main variable, STO. Table 2 presents the average of monthly returns for the equal- and value-weighted decile portfolios, in which stocks are sorted into deciles based on the short-term overreaction measure (STO). Decile 1 (low STO) consists of stocks with the lowest short-term overreaction measures in the preceding month, while decile 10 (high STO) comprises stocks with the highest short-term overreaction measures.

[Table 2] about here

The equal-weighted average of the raw return difference between deciles 1 and 10 is 0.77% per month, with the Newey and West (1987) *t*-statistic of 5.17. It is important to note that the average returns decrease almost linearly as the STO decile increases. The Carhart (1997) four-factor and Fama and French (2015) five-factor alpha of the long-short 1 − 10 long-short portfolio is 0.72% (*t*-stat = 3.81) and 0.73% (*t*-stat = 4.04), respectively, demonstrating economic and statistical significance. For the value-weighted portfolio, the return, four-factor alpha, and five-factor alpha difference between the lowest and highest STO decile portfolios are 0.90% (*t*-stat = 3.51), 0.79% (*t*-stat = 3.14), and 1.00% (*t*-stat = 3.72), respectively. In line with the equal-weighted portfolio returns, the return predictive power of our STO measure is strongly significant for the value-weighted portfolios.

To further investigate the relationship between short-term overreaction and future stock returns, we employ comprehensive bivariate-sort analyses by controlling for various well-known firm characteristics. The firm characteristic variables include short-term return reversal, bid-ask spread, the log of market capitalization, the market beta, the log of book-to-market ratio, intermediate-term momentum, illiquidity, stock turnover, idiosyncratic volatility, maximum daily return, the stock price. For example, to control for size, we construct quintile portfolios ranked by market capitalization. Within each size quintile, stocks are further sorted into quintile portfolios based on short-term overreaction, with quintile 1 (quintile 5) representing the stocks with the lowest (highest) STO. This ensures uniformity among firm sizes within the STO portfolios. Using this approach, we construct STO portfolios with comparable levels of firm size, effectively controlling for differences in size.

[Table 3] about here

Table 3 reports the results. Panel A (B) presents the results for the equal- (value-) weighted portfolios. For brevity, we refrain from reporting the returns for all 25 (5 × 5) portfolios.[2] In the first column of Panel A, in order to compare the results with other controlled results, we report the "No Control", which is equivalent to the univariate-sort results where stocks are sorted into quintiles by STO. In the second column of Panel A, we report the average return difference between high and low STO quintiles averaged across size quintiles. After controlling for size, the equal-weighted average return difference between high STO and low STO portfolios is 0.54% per month, with a corresponding Newey and West (1987) *t*-statistic of 4.61. Similarly, the 1 – 5 difference in four-factor alphas and five-factor alphas are at 0.47% and 0.50% per month, accompanied by a significant *t*-statistic of 3.22 and 3.55, respectively. When accounting for beta, book-to-market ratio, momentum, illiquidity, turnover, idiosyncratic volatility, maximum daily return, and price, the equal-weighted average raw return difference between the low and high STO quintiles ranges between 0.53% to 0.67%, with highly significant *t*-statistics between 4.35 to 5.43. These findings underscore the robust negative relationship between short-term overreaction and future stock returns, which persists even after accounting for diverse firm-specific characteristics.

Panel B of Table 3 reports the value-weighted raw and risk-adjusted returns on STO portfolios while accounting for the same cross-sectional effects outlined in Panel A of Table 3. For clarity and conciseness, we present the average returns aggregated across the five control quintiles,

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[2] To address concerns related to dependent bivariate sorts on correlated variables, which may not adequately control for the control variable, we employ two approaches. First, we conduct independent bivariate sorts on the two variables, yielding similar results. See Internet Appendix. Second, we conduct cross-sectional regressions incorporating all variables as control variables in Section 3.3.

ensuring the creation of quintile portfolios with dispersion in the STO while maintaining similar levels of the control variable. After controlling for size, book-to-market, momentum, and liquidity, the equal-weighted average return differences between the low- and high-STO portfolios are 0.53%, 0.58%, 0.61%, and 0.66% per month, respectively. These differences in average raw returns are both economically and statistically significant.

These findings suggest that, for both value-weighted and equal-weighted portfolios, well-known cross-sectional effects, such as size, book-to-market, momentum, and liquidity, cannot account for the low returns observed in high STO stocks.

3.2. Fama and Macbeth (1973) cross-sectional regressions

In the previous sections, we have validated the significance of short-term overreaction in predicting the cross-sectional pattern of future returns at the portfolio-sort analyses. This methodology, while avoiding the imposition of a specific functional form on the relationship between the STO and future returns, presents certain drawbacks. This poses challenges for simultaneously controlling multiple effects or factors. Consequently, we investigate the cross-sectional connection between STO and future returns at the individual stock level by controlling for well-known firm characteristics using Fama and MacBeth (1973) regressions.

For each month, we regress the monthly returns on the lagged value of STO and the control variables. We run the following equation:

$$ret_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} STO_{i,t} + \lambda_{2,t} V_{i,t} + \epsilon_{i,t+1}, \tag{3}$$

where $ret_{i,t+1}$ is the return on stock i in month t+1, $STO_{i,t}$ is the constructed short-term overreaction measure, for stock i in month t. The vector of control variables, $V_{i,t}$ includes short-term return reversal (RET), bid-ask spread (BAS), the log of market capitalization (ME), the market beta (BETA), the log of book-to-market ratio (BM), intermediate-term momentum (MOM), illiquidity (ILLIQ), stock turnover (TURN), idiosyncratic volatility (IVOL), maximum daily return (MAX), the stock price (PRC). The independent variables are winsorized at the 1% and 99% levels.

[Table 4] about here

Table 4 reports the time-series averages of the coefficients from Equation (3). Newey and West (1987) adjusted *t*-statistics are provided in parentheses. First, univariate regression findings indicate a significant and negative association between STO and future stock returns across the cross-section. The average slope, denoted as $\lambda_{1,t}$, in the monthly regressions of realized returns solely on STO is −0.254, with a corresponding *t*-statistic of −6.67. The observed economic impact is similar to the results presented in Table 2. According to the results, we find that the coefficient of STO is negative and significant at the 1% level, confirming our earlier results that upward (downward) investor overreaction predicts lower (higher) future returns.

The important findings are presented in Model 4 of Table 5, which reports the results for the model encompassing STO and various control variables. In this specification, the average slope coefficient on STO is −0.116, with a corresponding *t*-statistic of −4.27, which is still significant at the 1% level. It is important to note that the return predictive power of traditional and well-known short-term return reversal loses its power when our STO measure is included in the regression model.

In summary, the return predictability of STO remains significant after controlling for well-known determinants of cross-sectional returns including short-term return reversal and bid-ask spread. However, we need to further discuss whether short-term return reversal from Jegadeesh

(1990) can impact the predictive power of our measures.

3.3. Short-term return reversal and short-term overreaction

Our measure of investor overreaction is motivated by the idea that if short-term return reversal is driven by investor overreaction, then a more direct measure of investor overreaction based on trading volume can better predict future returns relative to past returns. Although our measure of short-term overreaction is based on trading volume rather than return, it has a positive correlation with one-month return (RET) because we multiply daily trading volume with the sign of contemporaneous daily return. Indeed, according to Panel B of Table 1, the average correlation between STO and RET is substantial at 0.461. We conduct double-sort analyses and Fama and MacBeth (1973) regressions to ensure that the return predictability of our measure does not merely reflect the return predictability of the past one-month return.

First, we explore the possibility that the return predictability of our measure of short-term overreaction may be driven by a one-month return reversal by performing four double-sort analyses, as shown in Table 5.

[Table 5] about here

Panel A of Table 5 shows the results of STO portfolio returns when RET is controlled. Specifically, we independently sort stocks into quintile portfolios based on STO and RET and we average out for each STO quintile portfolio. Panel A of Table 5 presents the returns of equal- and value-weighted portfolios, along with Newey and West (1987) *t*-statistics, respectively. We report the return and four-factor alpha differences between low- and high-STO portfolios, accounting for similar levels of short-term return reversal.

The equal-weighted average raw and risk-adjusted return differences between low and high

STO portfolios are notably more positive, with the four-factor and five-factor alphas of the equal-weighted portfolio at 0.30% (*t*-stat = 2.70) and 0.41% (*t*-stat = 3.35), respectively. These results show significantly greater economic and statistical significance in return and alpha differences, which is consistent with the univariate results reported in Table 2.

The value-weighted average raw return difference between the low and high STO quintiles is 0.35% per month, with a *t*-statistic of 1.90. The 1 − 5 STO difference in the four-factor alphas and five-factor alphas are also positive at 0.30% and 0.52% per month, with corresponding *t*-statistics of 2.00 and 2.54, respectively. Examining alpha differences individually for each RET quintile reveals an intuitive pattern. The STO effect tends to increase in magnitude as RET increases. Despite smaller magnitudes compared to previous findings, this is expected due to the high correlation between short-term return reversal and STO, leading to a significant reduction in STO spread after controlling for short-term return reversal. However, short-term return reversal alone does not fully explain the returns to low- and high-STO stocks.

Furthermore, we present the results of the double-sort analysis in Panel B of Table 5 to assess the explanatory power of short-term return reversal after accounting for STO. We average out for each RET quintile portfolio among 25 double-sorted portfolios. According to the results in Panel B, the analysis reveals that when controlling for STO, the average equal-weighted raw return difference between low and high RET portfolios is 0.30% per month, with a *t*-statistic of 1.42. The 1 − 5 difference in four-factor alphas is also positive at 0.25% per month and statistically insignificant.

For value-weighted portfolios, when STO is used as a control variable, the differences between raw and risk-adjusted returns on high short-term return reversal (RET) and low RET portfolios are positive and statistically insignificant, as shown in Panel B. According to the reversal strategy, a low future return is expected when the RET is high. However, when STO is controlled, the average return of low−high RET turns negative, which is surprising.

Moreover, we investigated the cross-sectional relationship between RET and expected returns at the individual firm level using Fama and MacBeth (1973) regressions, with the results reported in Table 4. Adding STO to the regression weakens the negative relationship between short-term return reversal and expected returns. Specifically, according to Model 3, the estimated average slope coefficient of RET becomes −0.104, with a Newey and West (1987) *t*-statistic of −1.26. This insignificant relationship between RET and future returns remains even after augmenting the regression with several control variables. However, according to Model 2, the coefficient of STO is −-0.210, with a corresponding *t*-statistic of −6.39, ensuring the significant predictive power of STO, regardless of whether RET is controlled. In summary, the cross-sectional regression results in Table 4 show that the effect of a short-term overreaction (STO) is not subsumed by that of a one-month return (RET).

On the one hand, previous literature has shown that the return predictive power of well-documented short-term return reversals is influenced by trading volume. Studies on short-term momentum and return reversals consistently suggest that the interplay between current returns and future returns is influenced significantly by trading volume. Medhat and Schmeling (2022) demonstrate through double sorting on the previous month's return and share turnover that significant short-term reversals are observed among low-turnover stocks, whereas high-turnover stocks tend to exhibit short-term momentum. Conrad et al. (1994) found that an increase in the number of transactions is associated with greater reversal on a weekly basis. Cooper (1999) reports less reversal among stocks with higher growth in trading volume on a weekly basis. Avramov et al. (2006) add that, after controlling for liquidity, higher turnover corresponds to more reversal in weekly returns but less reversal in monthly returns.

According to this body of literature, the return predictive power of short-term return reversals depends on the level of trading volume. This indicates that the interaction term between return reversal (RET) and stock turnover (TURN) has significant predictive power for future returns. Given that our study on Short-Term Overreaction (STO) shares similar fundamental principles as short-term return reversals, it is plausible that the predictive power of STO might be subsumed by the predictive power of TURN or the interaction term RET×TURN.

To address this hypothesis, Models 5 and 6 in Table 4 include both TURN and the interaction term RET×TURN in the cross-sectional regression analysis, with and without various control variables. Following Medhat and Schmeling (2022), we define TURN as the trading volume in month t divided by shares outstanding. Even with this additional control, the predictive power of STO remains robustly significant. For instance, Model 6 in Table 4 shows that the cross-sectional coefficient of STO remains significant, with a value of −0.099% and a corresponding *t*-statistic of −3.63, even after controlling the interaction between RET and TURN along with all other control variables.

Untabulated results from a 5 by 5 double sort (independent) based on TURN and STO further reveal that the predictive significance of STO diminishes but does not reverse as we move from low TURN to high TURN. These findings are largely consistent with the understanding that while STO is related to RET, it is not identical.

In summary, we find that the long-short portfolio returns based on RET are mostly insignificant, suggesting that the return predictability of one-month returns largely disappears after controlling for STO. Contrary to traditional short-term return reversal findings, stocks with high short-term return reversal exhibit lower future returns, aligning with expectations in a market influenced by poorly diversified and risk-averse investors.

Our study suggests that the previously observed negative relationship between RET and expected returns, as highlighted by Jegadeesh (1990), is attributable to RET acting as a proxy for STO. Moreover, our results confirm that while trading volume influences the predictive power of short-term return reversals, STO retains its significance as an independent predictor of future returns. The robustness of STO, even when accounting for RET and the interaction term RET× TURN, highlights its unique contribution to understanding short-term market dynamics.

3.4. Stock price reactions to subsequent earnings announcements

So far, we have assumed that our measure is a proxy of investor short-term overreaction while acknowledging that trading volume can capture both the extent of investor overreaction and uninformed trades. Therefore, the return predictability of our measure can be driven by investor overreaction and/or the compensation for risk-averse liquidity providers who take the opposite position of uninformed trades.

One important distinction between the implication of investor overreaction and that of uninformed trades is the prediction of the relation between STO and stock price reactions to subsequent public information announcements. If our measure captures investor overreaction, a positive (negative) STO indicates investors are overly optimistic (pessimistic) about the stock, implying that they will be on average negatively (positively) surprised by subsequent earnings announcements. This predicts that STO is a negative predictor of abnormal returns around subsequent earnings announcements. On the other hand, if the return predictability of STO is the compensation for liquidity providers that absorb uninformed trades, there is no reason why the effect of STO on future returns should be concentrated around public announcements such as earnings announcements. Thus, the liquidity provision story predicts that the relation between STO and the abnormal returns around the subsequent earnings announcement date should not differ from the relation between STO and the abnormal returns around any future date.

To test the idea, we conduct the following pooled-regression analysis:

$$CAR[-1,1]_{i,t+1} = \beta_{0,t} + \beta_{1,t}STO_{i,t} + \beta_{2,t}SUE_{i,t+1} + \beta_{3,t}Prior\ CAR[-1,1] + \beta_{4,t}V_{i,t} + \epsilon_{i,t}, \quad (4)$$

where dependent variable is the cumulative size-adjusted abnormal return (CAR) over the event window $[-1,1]$ of earnings announcement date. The independent variables include $STO_{i,t}$, the constructed overreaction variable, and the set of control variables. Control variables include those utilized in the Fama and Macbeth (1973) cross-sectional regression analysis in Table 4 as well as quarter and Friday fixed effects. We also include the standardized unexpected earnings, SUE, and the cumulative size-adjusted abnormal return over the event window $[-1,1]$ of the previous earnings announcement, $Prior\ CAR[-1,1]$. We calculate SUE as the quarter's actual earnings minus the average of the most recent analyst forecasts divided by the price per share at the quarter-end, following Livnat and Mendenhall (2006).

[Table 6] about here

We present the results of pooled regression in Table 6, Panel A. We find that STO is a significant negative predictor of 3-day abnormal returns around subsequent earnings announcements (CAR) after controlling for earnings surprise (SUE) and control variables. If STO negatively predicts CAR after controlling for SUE, it suggests that STO captures investor overreaction that goes beyond possible analyst expectation errors, as SUE would capture any bias in analyst expectations. The results in Panel A support the idea that STO is related to investors' overreaction and that their biased expectations get corrected when there is a public news arrival.

In Panel B, we use CAR[−1,1] of the same date of the previous month as the earnings announcement instead. For example, if a firm announced quarterly earnings on 5/23/2019, Panel A uses CAR[−1,1] around 5/23/2019 and Panel B uses CAR[−1,1] around 4/23/2019. If our results are driven by the compensation for liquidity providers that take the opposite position of uninformed trades, we should observe similar effects of STO on any 3-day abnormal returns. However, Panel B of Table 6 shows that STO has no significant effect on the 3-day abnormal returns around non-earnings announcement dates, contradicting the prediction of the liquidity provision story.

Overall, the results in Table 6 provide support for our overreaction story rather than the liquidity provision story. The results suggest that STO captures investors' short-term overreaction, and the return predictability of STO is driven by the subsequent correction of short-term overreaction.

3.5. Return predictability of STO in earnings announcement months

The results in Table 6 suggest that the return predictability of STO is likely driven by investor overreaction, which is subsequently corrected, especially when there are public information announcements such as earnings announcements. This implies that the timing of the public information arrival can play an important role in the return predictability of STO. To further explore this implication, we examine whether the STO portfolio returns and the cross-sectional regression results vary with the timing of earnings announcements in this subsection.

[Table 7] about here

In Panel A of Table 7, we compute equal- and value-weighted the STO decile portfolio returns as well as the 1 − 10 long-short portfolio returns and their four-factor and five-factor alphas, separately for the following three cases: 1) when there is an earnings announcement in month *t*

(STO calculation month), 2) when there is an earnings announcement in month *t*+1 (return measurement month), and 3) when no earnings announcement occurs in months *t* and *t*+1. We find that STO negatively predicts future returns when there are earnings announcements in month *t*+1 or when there is no earnings announcement in months *t* and *t*+1 (Panels A2 and A3). On the other hand, the return predictability of STO largely disappears when there is an earnings announcement in month *t* (Panel A1). The Fama and Macbeth (1973) cross-sectional regressions presented in Panel B show similar results that there is no significant relation between STO and future returns when there is an earnings announcement during the STO measurement month (month *t*).

If investors' short-term overreaction as measured by STO is partly corrected when there is an earnings announcement, as Table 6 shows, it is possible that STO calculated in the month of the earnings announcement captures the correction in response to public information rather than the overreaction. It is also possible that STO captures investor reactions to public information (earnings news) when there is an earnings announcement during the STO measurement month. If this is the case, the results appear to be consistent with Daniel and Titman (2006) and Da et al. (2014), which suggest that the return predictability of overreaction is largely driven by investor overreaction to intangible information rather than investor overreaction to tangible (public) information.

4. Additional analysis

4.1. Subsample analysis

In this section, we conduct additional tests to explore when the return predictability of STO is stronger. First, we investigate whether the predictive power of STO differs across different investor sentiment states using the investor sentiment index proposed by Baker and Wurgler (2006).

Prior literature shows that investor sentiment can be related to speculative behavior and is closely linked to market mispricing (e.g., Aboody et al., 2018, Baker and Wurgler 2006, Da et al., 2015, Stambaugh et al., 2012).

We obtain monthly investor sentiment data from Wurgler's website[3] and divide the sample into two subsamples based on the monthly sentiment index. High-sentiment months are defined as those with an investor sentiment index above the sample median, and low-sentiment months are those with an index below the sample median.

[Table 8] about here

Panel A of Table 8 shows that the predictive power of the STO is statistically significant in both high and low-investor sentiment states. In addition, the STO strategy yields greater profitability in periods characterized by high sentiment than those with low sentiment. For example, the four-factor and five-factor alphas of the value-weighted $1-10$ long-short portfolio returns are 1.16% and 1.48% respectively for high-sentiment months, while they are 0.59% and 0.60% respectively. The difference between the high and low sentiment months is more pronounced in the short leg of the long-short portfolio (STO decile 10). The results are consistent with the prior studies that anomaly strategies, especially the short leg of the strategy, are more profitable following high-sentiment periods (e.g., Stambaugh et al., 2012).

Next, we classify stocks into three distinct sets of subsamples based on firm characteristics and evaluate the performance of the STO strategy by calculating the STO decile portfolio returns within each subsample. Panels B, C, and D of Table 8 report the STO decile portfolio returns for the three sets of subsamples based on institutional ownership (Panel B), firm size (Panel C), and illiquidity (Panel D). We find that there is no consistent difference between the high institutional

[3] https://pages.stern.nyu.edu/~jwurgler/

ownership and low institutional ownership stocks in the profitability of the STO strategy. For instance, the five-factor alpha of the equal-weighted long-short portfolio return is 0.64% (0.74%) for high (low) institutional ownership stocks, while the five-factor alpha of the value-weighted long-short portfolio return is 0.85% (0.32%) for high (low) institutional ownership stocks. On the other hand, STO portfolio returns of the subsamples split by firm size and by illiquidity show that the STO strategy is more profitable for small and illiquid firms. Taken together, the results suggest that the return predictability of STO is generally more profitable when we expect mispricing to be more pronounced.

4.2. Short side and long side of STO

There are a couple of interesting patterns we observe in the STO strategy returns. The results in Table 2 show that the value-weighted long-short STO strategy returns are consistently higher than the equal-weighted long-short STO strategy returns across all measures of return. Moreover, we observe that the long leg (STO decile 1) outperforms the short leg in the equal-weighted returns, while the short leg (STO decile 10) outperforms the long leg in the value-weighted returns.

To gain a better understanding of how the long and short legs of the STO strategy perform and the possible drivers of their returns, we perform a quantile portfolio sort analysis in Table 9. We first sort stocks based on the STO measure and set the third quantile as the neutral portfolio. Using this neutral portfolio as a reference, the difference between the third and fifth quantiles ($3 - 5$) represents the return on the short leg of the STO strategy, while the difference between the first and third quantiles ($1 - 3$) represents the return on the long leg.

[Table 9] about here

Panel A of Table 9 provides the performance of the long and short legs of the STO strategy. The results confirm our observation that the equal-weighted returns are stronger on the long leg, whereas the value-weighted returns are more robust on the short leg. For instance, the equal-weighted long leg (1 − 3) return is 0.48% with a t-statistic of 4.96, compared to the short leg (3 − 5) return of 0.13% with a t-statistic of 1.50. Conversely, the short leg (3 − 5) of the value-weighted returns shows a stronger performance, posting a return of 0.43% with a t-statistic of 2.80, while the long leg (1 − 3) return is 0.22% with a *t*-statistic of 1.91.

To understand the differing patterns of equal-weighted and value-weighted returns in the long and short legs, we examine the results by institutional ownership (IO) subsamples presented in Panel B of Table 9. This panel reports the STO 1 − 5 return as well as the long and short leg returns for each IO quintile. Panel B1 shows that the equal-weighted STO long-short returns (1 − 5) decrease as we move from low to high IO, whereas the value-weighted returns increase from low to high IO. For example, the equal-weighted 1 − 5 return is 0.80% (*t*-stat = 3.65) for low IO stocks (IO quintile 1), and 0.51% (*t*-stat = 3.59) for high IO stocks (IO quintile 5). In contrast, the value-weighted 1 − 5 return is 0.46% (*t*-stat = 1.62) for low IO stocks (IO quintile 1) and 0.66% (*t*-stat = 3.56) for high IO stocks (IO quintile 5).

Panel B2 shows that the short leg (3 − 5) returns increase from low to high IO. Particularly, the value-weighted short leg is stronger in high IO, contributing to the overall strength of the value-weighted returns. For instance, the value-weighted 3 − 5 return is 0.51% (*t*-stat = 4.26) in high IO, compared to 0.08% (*t*-stat = 0.36) in low IO. These results challenge the classical argument that anomaly returns should be weaker for high IO stocks because sophisticated investors trade against mispricing, but are consistent with the rational speculation theory (e.g., DeLong et al. 1990, Abreu and Brunnermeir 2002, 2003) that rational investors may optimally choose to buy overvalued stocks. Jang and Kang (2019) present evidence supporting the rational speculation theory that institutional investors tend to buy an overvalued security until its price reaches the peak of the bubble, aligning with our finding that the STO short leg returns are stronger for high IO stocks, especially in value-weighted returns.

Panel B3 shows that the long leg $(1 - 3)$ returns are stronger among low IO stocks, particularly for equal-weighted returns. For example, the equal-weighted $1 - 3$ return for low IO stocks is 0.93% (t-stat = 5.04), while it is only 0.25% (t-stat = 2.18) for high IO stocks. This pattern aligns with the classical argument that underpricing is more prevalent among low IO stocks.

In summary, the STO effect in the short leg (positive overreaction) appears to be strengthened by rational speculation by institutional investors, leading to stronger performance among high IO stocks. In contrast, the long leg (negative overreaction) leads to underpricing that does not lead to rational speculation, therefore the return of the long leg is more pronounced among low IO stocks. This distinction may explain why the STO effect is more robust in value-weighted returns than in equal-weighted returns.

4.3. Alternative measure of STO

In this section, we examine whether the observed predictive power of STO is sensitive to the weighting of daily signed volume within each month in the construction process. Specifically, we examine whether the predictive power of STO remains significant when the daily signed volume is equal-weighted (set W_d to $1/D$ in Equation (2) of Section 2.1) as opposed to being weighted higher toward the end of the month.

[Table 10] about here

Table 10 shows STO decile portfolio returns when STO is constructed based on the equal-weighted average of daily signed volume. We find that the results are qualitatively similar to the results in Table 2 but smaller in magnitude. The equal-weighted average of the raw return difference between deciles 1 and 10 is 0.51% per month, with the Newey and West (1987) *t*-statistic of 4.28. Similar to the results using the weighted average STO, the average returns decrease almost linearly as the STO decile increases. The Carhart (1997) four-factor and Fama and French (2015) five-factor alphas are 0.42% (*t*-stat = 2.74) and 0.40% (*t*-stat = 2.56), respectively, demonstrating economic and statistical significance. The value-weighted return, four-factor alpha, and five-factor alpha differences between the highest and lowest STO decile portfolios are 0.68% (*t*-stat = 2.61), 0.57% (*t*-stat = 2.14), and 0.67% (*t*-stat = 2.68), respectively.

In summary, the results in Table 10 suggest the reliability of our results and the resilience of our STO measure in capturing return predictability across alternative return calculation. The robustness of our results is confirmed by consistent findings when employing the equal-weighted average of daily signed volume when calculating returns.

5. Conclusion

Our study introduces a novel predictor of short-term stock returns based on weighted daily signed volume, termed Short-Term Overreaction (STO). We find that STO predicts subsequent stock returns, with stocks exhibiting upward (downward) short-term overreactions experiencing negative (positive) future returns. Importantly, the predictive power of STO remains significant even after controlling for the past one-month return, suggesting that the effect of STO is not subsumed by short-term return reversal. Fama and Macbeth (1973) cross-sectional regressions further confirm that STO is a negative predictor of cross-sectional returns. Additionally, we demonstrate that STO is a significant negative predictor of 3-day abnormal returns around subsequent earnings announcements, indicating that investors are overly optimistic (pessimistic) about high (low) STO stocks. On the other hand, STO is not significantly related to 3-day abnormal returns around non-earnings announcement dates, which suggests that the effect of STO is not driven by the compensation for liquidity providers. The subsample results show that the return predictability of STO tends to be stronger when we expect market mispricing to be more pronounced, such as in periods of high investor sentiment and for small and illiquid stocks. Overall, our findings provide empirical evidence supporting STO as a more direct measure of investor overreaction, shedding light on the dynamics of investor overreaction and its return predictability.

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Appendix. Variable Descriptions

Table A. Variable Descriptions

$RET_{i,t}$	$RET_{i,t}$ is the return of stock *i* in month *t*.
$BAS_{i,t}$	$BAS_{i,t}$ is the bid-ask spread for stock *i* in month *t*.
$BM_{i,t}$	$BM_{i,t}$ is the natural logged value of the firm's book-to-market ratio from the fiscal year ending at least six months prior to month *t* by following Fama and French (1992).
$ME_{i,t}$	$ME_{i,t}$ is the natural logged value of the stock *i*'s market capitalization being defined as the total number of shares outstanding for firm *i* multiplied by the share price, on the last day of month *t* by following Fama and French (1992).
$BETA_{i,t}$	$BETA_{i,t}$ is the stock *i*'s market beta in month *t*, which is computed by regressing stock *i*'s daily returns on the current daily market return, as well as the lag and lead market returns to control for nonsynchronous trading, following the methods of Scholes and Williams (1977) and Dimson (1979). $$ret_{i,d} - ret_{f,d} = \alpha_i + \beta_{1,i} \cdot mktrf_{d-1} + \beta_{2,i} \cdot mktrf_d + \beta_{3,i} \cdot mktrf_{d+1} + \epsilon_{i,d}$$ where $ret_{i,d}$ is the return on stock *i* on day *d* and $ret_{f,d}$ is the T-Bill return on day *d*. $mktrf_{d-1}$, $mktrf_d$, and $mktrf_{d+1}$ are the excess market return from the previous, current, and future relative to risk-free rate respectively. *BETA* of stock *i* at the end of the month *t* is calculated by $\widehat{\beta_{1,\iota}} + \widehat{\beta_{2,\iota}} + \widehat{\beta_{3,\iota}}$.
$IVOL_{i,t}$	$IVOL_{i,t}$ is the standard deviation of the daily residuals obtained from the Fama and French (1993) three-factor model for that month, by following Ang et al. (2006). $$ret_{i,d} - ret_{f,d} = \alpha_i + \beta_{1,i} \cdot mktrf_d + \beta_{2,i} \cdot SMB_d + \beta_{1,i} \cdot HML_d + \epsilon_{i,d}$$ where $ret_{i,d}$ is the return on stock *i* on day *d* and $ret_{f,d}$ is the T-Bill return on day *d*. $mktrf_d$, SMB_d, and HML_d are daily three-factors from Fama and French (1993). $IVOL_{i,t}$ of stock *i* at the end of the month *t* is defined as the standard deviation of daily residuals, $\epsilon_{i,d}$ in month *t*.
$ILLIQ_{i,t}$	$ILLIQ_{i,t}$ is the firm's illiquidity measure by following Amihud (2002) defined as follows: $$ILLIQ_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{\lvert ret_{i,d} \rvert}{dollar\ volume_{i,d}},$$ where $ret_{i,d}$ is stock *i*'s return on day *d*, $dollar\ volume_{i,d}$ is the corresponding daily volume in dollars, and $D_{i,t}$ is the number of days for which data are available for stock *i* in month *t*.
$MOM_{i,t}$	$MOM_{i,t}$ is the intermediate-term of momentum, which is stock *i*'s return over months (*t*−12,*t*−1), following Jegadeesh and Titman (1993).
$TURN_{i,t}$	$TURN_{i,t}$ is the monthly share turnover of stock *i*, computed as the number of shares traded in month *t* divided by the total number of shares outstanding.
$IO_{i,t}$	$IO_{i,t}$ is the institutional ownership is characterized by the proportion of a company's shares held by institutional investors in the quarter preceding month *t*, relative to the total number of shares in circulation.
$MAX_{i,t}$	$MAX_{i,t}$ is the maximum daily return of a stock in month *t*, following Bali et al. (2011).
$PRC_{i,t}$	$PRC_{i,t}$ is the price of stock *i* at the end of month *t*.

Table 1. Summary statistics

This table reports average stock characteristics for decile portfolios sorted by each short-term overreaction (STO) measure. We sort stocks into decile portfolios based on STO, where STO is a newly constructed volume-based short-term overreaction measure. Panel A reports the monthly average of the STO measure, short-term return reversal (RET), bid-ask spread (BAS), the log of market capitalization (ME), the market beta (BETA), the log of book-to-market ratio (BM), intermediate-term momentum (MOM), illiquidity (ILLIQ), stock turnover (TURN), idiosyncratic volatility (IVOL), maximum daily return (MAX), and the stock price (PRC) for each STO decile portfolio. Panel B reports the time-series average of cross-sectional correlations between firm characteristics that are utilized in Panel A. The detailed variable definitions are provided in Section 2 and Appendix. The sample period is from May 1993 to December 2022.

Panel A: Summary statistics

STO decile	STO	RET	BAS	ME	BETA	BM	MOM	ILLIQ	TURN	IVOL	MAX	PRC
1 (Low)	−0.61	−0.10	0.04	311.20	0.85	0.77	0.27	6.23	1.53	0.03	0.06	28.81
2	−0.33	−0.06	0.04	448.65	0.98	0.70	0.25	2.73	1.63	0.03	0.06	50.62
3	−0.21	−0.04	0.04	514.25	1.02	0.68	0.22	2.18	1.68	0.02	0.06	58.11
4	−0.12	−0.02	0.04	529.85	1.02	0.68	0.19	2.13	1.70	0.02	0.07	47.02
5	−0.04	−0.00	0.04	527.22	1.03	0.67	0.17	1.78	1.69	0.02	0.07	54.57
6	0.04	0.02	0.04	538.00	1.03	0.68	0.14	1.81	1.72	0.02	0.07	49.90
7	0.12	0.04	0.04	531.29	0.99	0.68	0.12	1.95	1.74	0.03	0.07	43.42
8	0.21	0.06	0.04	521.04	0.97	0.69	0.09	2.18	1.73	0.03	0.08	50.13
9	0.33	0.09	0.04	463.67	0.90	0.71	0.07	3.01	1.84	0.03	0.08	44.39
10 (High)	0.63	0.16	0.05	307.13	0.67	0.80	0.03	6.26	2.76	0.03	0.11	35.01

Panel B: Correlations

	STO	RET	BAS	ME	BETA	BM	MOM	ILLIQ	TURN	IVOL	MAX	PRC
STO	1											
RET	0.461	1										
BAS	0.030	0.073	1									
ME	−0.001	0.002	−0.096	1								
BETA	−0.024	−0.004	0.065	0.007	1							
BM	0.015	0.032	0.055	−0.058	−0.029	1						
MOM	−0.102	−0.014	−0.034	0.012	0.046	0.068	1					
ILLIQ	0.003	0.003	0.124	−0.011	−0.024	0.050	−0.027	1				
TURN	0.008	0.033	0.047	−0.001	0.024	−0.003	0.014	−0.004	1			
IVOL	0.070	0.226	0.772	−0.092	0.026	0.075	−0.050	0.124	0.076	1		
MAX	0.142	0.390	0.621	−0.061	0.050	0.058	−0.043	0.093	0.089	0.902	1	
PRC	−0.000	0.001	−0.019	0.100	−0.001	−0.002	0.002	−0.002	−0.001	−0.016	−0.011	1

Table 2. STO portfolio returns

This table reports the average monthly excess returns, Carhart (1997) four-factor alphas, and Fama and French (2015) five-factor alphas of each decile portfolio sorted by the short-term overreaction (STO) measure. At the end of each month *t*, we sort stocks into decile portfolios based on the STO measure over the month, where STO is our measure of short-term overreaction as defined in Section 2.1. We report the average returns and alphas of the decile portfolios in month *t*+1. Panel A (B) reports the results of equal-weighted (value-weighted) schemes. The column labeled "1 − 10" represents the difference in average returns and alphas between the top and the bottom STO decile portfolio. The numbers within parentheses indicate Newey and West (1987) corrected *t*-statistics with 12 lags. The sample period is from May 1993 to December 2022. The sample period is from May 1993 to December 2022.

	STO decile										
	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	1−10
Panel A: Equal-weighted portfolio											
Excess	1.41	1.11	0.96	0.90	0.85	0.72	0.71	0.70	0.67	0.64	0.77
return	(4.50)	(3.44)	(3.11)	(2.84)	(2.65)	(2.23)	(2.19)	(2.09)	(1.93)	(1.88)	(5.17)
4−factor	0.71	0.35	0.17	0.11	0.08	−0.05	−0.07	−0.06	−0.05	−0.00	0.72
alpha	(4.40)	(2.77)	(1.91)	(1.33)	(1.14)	(−0.74)	(−0.91)	(−0.62)	(−0.48)	(−0.03)	(3.81)
5−factor	0.65	0.32	0.16	0.08	0.06	−0.09	−0.15	−0.08	−0.15	−0.08	0.73
alpha	(4.40)	(2.43)	(1.59)	(0.88)	(0.74)	(−1.13)	(−2.14)	(−0.83)	(−1.35)	(−0.65)	(4.04)
Panel B: Value-weighted portfolio											
Excess	1.09	0.93	1.03	0.93	0.83	0.71	0.63	0.53	0.40	0.19	0.90
return	(3.96)	(3.59)	(4.11)	(3.76)	(3.01)	(2.60)	(2.13)	(1.96)	(1.41)	(0.57)	(3.51)
4−factor	0.33	0.18	0.29	0.15	0.11	−0.01	−0.12	−0.22	−0.29	−0.46	0.79
alpha	(2.48)	(1.85)	(3.18)	(1.88)	(1.55)	(−0.10)	(−1.53)	(−3.00)	(−2.51)	(−2.75)	(3.14)
5−factor	0.37	0.15	0.30	0.22	0.09	−0.06	−0.13	−0.24	−0.39	−0.63	1.00
alpha	(2.57)	(1.31)	(3.75)	(2.36)	(1.32)	(−0.72)	(−1.80)	(−3.54)	(−2.80)	(−2.97)	(3.72)

Table 3. STO portfolio returns after controlling for various firm characteristic variables

This table presents the average monthly returns using the dependent bivariate-sort methodology based on the short-term overreaction (STO) measure after controlling for several variables. The sorting is based on short-term overreaction, after controlling for short-term return reversal (RET), bid-ask spread (BAS), the log of market capitalization (ME), the market beta (BETA), the log of book-to-market ratio (BM), intermediate-term momentum (MOM), illiquidity (ILLIQ), stock turnover (TURN), idiosyncratic volatility (IVOL), maximum daily return (MAX), and the stock price (PRC). First, stocks are sorted into quintiles using the control variable, and within each quintile, they are further sorted based on the short-term overreaction from the previous month. Quintile 1 (5) comprises stocks with the lowest (highest) STO. Panel A (B) reports the results of equal-weighted (value-weighted) schemes. The table reports the average returns across the control quintiles, ensuring dispersion in STO while maintaining similar levels of the control variable. The row labeled "1 − 5," "1 − 5 FF4 alpha," and "1 − 5 FF5 alpha" represent the difference in returns, Carhart (1997) four-factor alphas, and Fama and French (2015) five-factor alphas between the top and bottom quintile sorted by STO for each quintile sorted by control variables. The numbers within parentheses indicate Newey and West (1987) corrected *t*-statistics with 12 lags. The sample period is from May 1993 to December 2022.

Panel A: Equal-weighted portfolio

STO quintile	No control	RET	BAS	ME	BETA	BM	MOM	ILLIQ	TURN	IVOL	MAX	PRC
1 (Low)	1.26	1.11	1.28	1.21	1.26	1.28	1.24	1.23	1.28	1.30	1.25	1.25
2	0.93	0.99	0.96	0.93	0.92	0.93	0.92	0.91	0.92	0.94	0.90	0.95
3	0.78	0.87	0.79	0.79	0.80	0.81	0.75	0.77	0.80	0.76	0.80	0.80
4	0.71	0.70	0.67	0.73	0.68	0.71	0.71	0.75	0.67	0.71	0.70	0.73
5 (High)	0.66	0.67	0.63	0.67	0.68	0.61	0.71	0.68	0.67	0.64	0.69	0.62
1 − 5	0.61	0.44	0.66	0.54	0.58	0.67	0.53	0.55	0.62	0.66	0.56	0.63
	(4.76)	(3.82)	(5.06)	(4.61)	(4.87)	(5.25)	(4.35)	(4.50)	(4.73)	(5.43)	(4.67)	(5.20)
1 − 5	0.56	0.43	0.60	0.47	0.55	0.62	0.52	0.50	0.55	0.60	0.48	0.56
FF4 alpha	(3.42)	(4.00)	(3.87)	(3.22)	(3.69)	(3.91)	(3.43)	(3.19)	(3.40)	(4.00)	(3.30)	(3.90)
1 − 5	0.60	0.50	0.62	0.50	0.57	0.65	0.46	0.52	0.60	0.64	0.57	0.58
FF5 alpha	(3.77)	(4.15)	(4.30)	(3.55)	(3.84)	(4.15)	(2.88)	(3.34)	(3.91)	(4.46)	(3.89)	(4.01)

Panel B: Value-weighted portfolio

STO quintile	No control	RET	BAS	ME	BETA	BM	MOM	ILLIQ	TURN	IVOL	MAX	PRC
1 (Low)	0.99	0.92	0.91	1.16	0.97	1.03	0.94	1.12	1.02	0.84	0.83	1.02
2	0.98	0.91	0.86	0.90	0.94	1.00	0.85	0.79	0.99	0.79	0.88	0.96
3	0.77	0.77	0.75	0.77	0.75	0.86	0.69	0.66	0.83	0.65	0.74	0.76
4	0.59	0.59	0.66	0.68	0.59	0.59	0.56	0.64	0.57	0.59	0.61	0.64
5 (High)	0.34	0.45	0.28	0.62	0.43	0.45	0.32	0.46	0.34	0.32	0.37	0.56
1 − 5	0.65	0.47	0.62	0.53	0.54	0.58	0.61	0.66	0.68	0.52	0.46	0.46
	(3.79)	(2.98)	(3.86)	(4.59)	(3.74)	(4.00)	(3.77)	(5.69)	(4.37)	(3.56)	(2.70)	(2.65)
1 − 5	0.57	0.40	0.52	0.49	0.48	0.51	0.59	0.62	0.61	0.44	0.32	0.40
FF4 alpha	(3.27)	(2.79)	(2.97)	(3.35)	(3.09)	(3.61)	(2.99)	(4.34)	(3.59)	(2.78)	(1.91)	(2.01)
1 − 5	0.68	0.60	0.61	0.52	0.54	0.58	0.55	0.62	0.64	0.52	0.47	0.44
FF5 alpha	(3.49)	(3.43)	(3.61)	(3.64)	(3.35)	(3.98)	(2.88)	(4.73)	(4.07)	(3.18)	(2.71)	(2.24)

Table 4. Fama and MacBeth (1973) cross-sectional regressions

This table presents the results of the Fama and Macbeth (1973) cross-sectional regression. We report the time-series averages of the monthly regression coefficients from the regression of the return on stock *i* in month *t*+1 on our short-term overreaction measure, STO, and control variables. Controls include short-term return reversal (RET), stock turnover (TURN), bid-ask spread (BAS), the log of market capitalization (ME), the market beta (BETA), the log of book-to-market ratio (BM), intermediate-term momentum (MOM), illiquidity (ILLIQ), idiosyncratic volatility (IVOL), maximum daily return (MAX), and the stock price (PRC). The independent variables are winsorized at the 1% and 99% levels. The numbers within parentheses indicate Newey and West (1987) corrected *t*-statistics with 12 lags. The detailed definitions of the variables are available in the Appendix. The sample period is from May 1993 to December 2022.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
STO	−0.254	−0.210	−0.220	−0.116	−0.211	−0.099
	(−6.67)	(−6.39)	(−5.62)	(−4.27)	(−5.90)	(−3.63)
RET			−0.104	−0.261	−0.126	−0.311
			(−1.26)	(−4.66)	(−1.46)	(−4.58)
RET×TURN					0.063	0.080
					(2.12)	(3.09)
TURN					−0.156	−0.018
					(−1.44)	(−0.33)
BAS		−0.273		−0.296		−0.298
		(−1.67)		(−1.81)		(−1.93)
ME		−0.077		−0.079		−0.068
		(−1.37)		(−1.40)		(−1.22)
BETA		0.034		0.014		0.012
		(1.11)		(0.48)		(0.43)
BM		0.133		0.133		0.142
		(1.70)		(1.69)		(1.81)
MOM		0.277		0.283		0.278
		(3.14)		(3.19)		(3.28)
ILLIQ		−0.038		−0.042		−0.035
		(−0.95)		(−1.03)		(−0.86)
IVOL		−0.057		−0.161		−0.137
		(−0.75)		(−2.00)		(−1.66)
MAX		−0.234		−0.063		−0.050
		(−2.66)		(−0.78)		(−0.63)
PRC		−0.103		−0.080		−0.090
		(−1.95)		(−1.50)		(−1.68)

Table 5. Bivariate-sort analysis of STO and RET

This table presents the average monthly excess returns using the dependent double-sort method based on the short-term overreaction (STO) measure and short-term return reversal (RET). Stocks are independently sorted into quintile portfolios based on two variables. In Panel A (B), we report the results of STO (RET) returns for both equal-weighted and value-weighted portfolios. The table reports the average monthly excess returns for the 25 portfolios generated through the independent double-sort method. The columns labeled "1 − 5," "1 − 5 FF4 alpha," and "1 − 5 FF5 alpha" represent differences in the returns, Carhart (1997) four-factor alphas, and Fama and French (2015) five-factor alphas. The row "Average" is the average value of portfolio returns sorted by one variable for each quintile sorted by the other variable. STO is a volume-based short-term overreaction measure, and RET is defined as the measure of short-term return reversal. The numbers within parentheses indicate Newey and West (1987) corrected *t*-statistics with 12 lags. The sample period is from May 1993 to December 2022.

Panel A: STO portfolio returns controlling for RET

Equal-weighted portfolio

		STO							
		1 (Low)	2	3	4	5 (High)	1 − 5	1 − 5 FF4 alpha	1 − 5 FF5 alpha
RET	1 (Low)	1.53	0.95	0.52	0.65	0.90	0.63	0.59	0.66
		(3.93)	(2.29)	(1.18)	(1.39)	(1.77)	(2.64)	(2.24)	(2.42)
	2	1.20	1.02	0.85	0.71	0.66	0.55	0.55	0.61
		(4.36)	(3.43)	(2.64)	(2.02)	(1.75)	(3.29)	(3.68)	(3.71)
	3	1.08	0.96	0.90	0.79	0.83	0.24	0.27	0.33
		(4.04)	(3.55)	(3.21)	(2.62)	(2.65)	(1.92)	(2.18)	(2.73)
	4	0.86	0.82	0.87	0.72	0.88	−0.02	0.00	0.15
		(3.41)	(2.90)	(3.01)	(2.38)	(2.90)	(−0.14)	(0.03)	(1.16)
	5 (High)	0.49	0.83	0.67	0.64	0.42	0.07	0.08	0.30
		(1.09)	(2.07)	(1.70)	(1.68)	(1.07)	(0.28)	(0.27)	(1.06)
	Average	1.03	0.92	0.76	0.70	0.74	0.29	0.30	0.41
		(3.42)	(2.93)	(2.32)	(2.03)	(2.06)	(2.67)	(2.70)	(3.35)

Value-weighted portfolio

		STO							
		1 (Low)	2	3	4	5 (High)	1 − 5	1 − 5 FF4 alpha	1 − 5 FF5 alpha
RET	1 (Low)	0.88	0.64	0.42	0.70	0.83	0.04	0.17	0.25
		(2.59)	(1.63)	(0.96)	(1.63)	(1.29)	(0.09)	(0.41)	(0.58)
	2	1.06	1.10	0.81	0.62	0.92	0.14	0.09	0.35
		(3.88)	(4.14)	(2.74)	(2.13)	(2.50)	(0.56)	(0.37)	(1.74)
	3	0.90	0.83	0.87	0.63	0.45	0.45	0.43	0.55
		(3.24)	(3.38)	(3.33)	(2.30)	(1.82)	(2.24)	(2.20)	(2.38)
	4	1.03	0.91	0.81	0.66	0.46	0.57	0.45	0.76
		(4.92)	(3.27)	(2.84)	(2.34)	(1.59)	(2.03)	(1.85)	(2.60)
	5 (High)	0.88	0.92	0.99	0.51	0.31	0.57	0.39	0.71
		(1.89)	(1.95)	(2.53)	(1.33)	(1.01)	(1.22)	(0.91)	(1.41)
	Average	0.95	0.88	0.78	0.62	0.59	0.35	0.30	0.52
		(3.72)	(3.18)	(2.62)	(2.15)	(1.89)	(1.90)	(2.00)	(2.54)

Panel B: RET portfolio returns controlling for STO

Equal-weighted portfolio

		RET							
		1 (Low)	2	3	4	5 (High)	1 − 5	1 − 5 FF4 alpha	1 − 5 FF5 alpha
STO	1 (Low)	1.53	1.20	1.08	0.86	0.49	1.04	0.90	0.64
		(3.93)	(4.36)	(4.04)	(3.41)	(1.09)	(3.45)	(2.28)	(1.76)
	2	0.95	1.02	0.96	0.82	0.83	0.12	0.08	−0.23
		(2.29)	(3.43)	(3.55)	(2.90)	(2.07)	(0.47)	(0.33)	(−0.65)
	3	0.52	0.85	0.90	0.87	0.67	−0.15	−0.13	−0.37
		(1.18)	(2.64)	(3.21)	(3.01)	(1.70)	(−0.68)	(−0.49)	(−1.26)
	4	0.65	0.71	0.79	0.72	0.64	0.00	−0.02	−0.23
		(1.39)	(2.02)	(2.62)	(2.38)	(1.68)	(0.02)	(−0.08)	(−0.76)
	5 (High)	0.90	0.66	0.83	0.88	0.42	0.48	0.39	0.28
		(1.77)	(1.75)	(2.65)	(2.90)	(1.07)	(1.61)	(1.24)	(0.79)
	Average	0.91	0.89	0.91	0.83	0.61	0.30	0.25	0.02
		(2.12)	(2.80)	(3.26)	(2.99)	(1.58)	(1.42)	(1.00)	(0.06)

Value-weighted portfolio

		RET							
		1 (Low)	2	3	4	5 (High)	1 − 5	1 − 5 FF4 alpha	1 − 5 FF5 alpha
STO	1 (Low)	0.88	1.06	0.90	1.03	0.88	−0.01	0.02	−0.25
		(2.59)	(3.88)	(3.24)	(4.92)	(1.89)	(−0.01)	(0.05)	(−0.53)
	2	0.64	1.10	0.83	0.91	0.92	−0.28	−0.32	−0.65
		(1.63)	(4.14)	(3.38)	(3.27)	(1.95)	(−0.59)	(−0.61)	(−1.37)
	3	0.42	0.81	0.87	0.81	0.99	−0.57	−0.64	−0.82
		(0.96)	(2.74)	(3.33)	(2.84)	(2.53)	(−1.62)	(−1.63)	(−1.91)
	4	0.70	0.62	0.63	0.66	0.51	0.19	0.19	−0.36
		(1.63)	(2.13)	(2.30)	(2.34)	(1.33)	(0.64)	(0.59)	(−1.07)
	5 (High)	0.83	0.92	0.45	0.46	0.31	0.52	0.24	0.21
		(1.29)	(2.50)	(1.82)	(1.59)	(1.01)	(0.90)	(0.47)	(0.39)
	Average	0.69	0.90	0.73	0.77	0.72	−0.03	−0.10	−0.37
		(1.75)	(3.38)	(3.05)	(3.33)	(2.13)	(−0.10)	(−0.33)	(−1.17)

Table 6. STO and the abnormal return around subsequent earnings announcement

Panel A of Table 6 presents the results of the pooled regression of abnormal returns around subsequent earnings announcement dates on STO and control variables. The dependent variable is the cumulative size-adjusted abnormal return (CAR) over the event window [−1,1] of the earnings announcement date. The independent variables include the standardized unexpected earnings (SUE), defined as the quarter's actual earnings minus the average of the most recent analyst forecasts divided by the stock price, the prior quarter's CAR[−1,1], and the short-term overreaction (STO). The set of control variables includes short-term return reversal (RET), bid-ask spread (BAS), the log of market capitalization (ME), the market beta (BETA), the log of book-to-market ratio (BM), intermediate-term momentum (MOM), illiquidity (ILLIQ), stock turnover (TURN), idiosyncratic volatility (IVOL), maximum daily return (MAX), the stock price (PRC), and Friday and quarter fixed effects. Panel B reports the results when we use abnormal returns around the same date of the previous month of earnings announcement as the dependent variable. All independent variables are standardized and winsorized at the 1% and 99% levels. The analysis accounts for Friday and quarter fixed effects, and firm clustering is applied. The *t*-statistics in parentheses are based on standard errors clustered at the firm level. The sample period is from May 1993 to December 2022.

Panel A: Abnormal returns around the actual earnings announcement date

	(1) CAR[−1,1]	(2) CAR[−1,1]	(3) CAR[−1,1]	(4) CAR[−1,1]	(5) CAR[−1,1]	(6) CAR[−1,1]
STO	−0.06***	−0.04**	−0.02**	−0.05**	−0.05**	−0.06**
	(−3.12)	(−2.02)	(−1.91)	(−2.31)	(−2.28)	(−2.14)
SUE			3.58***			3.60***
			(45.35)			(45.25)
Prior CAR[−1,1]			−0.02		0.15***	−0.01
			(−0.83)		(5.44)	(−0.19)
RET		−0.03	−0.11	−0.01	−0.01	−0.08*
		(−1.11)	(−1.22)	(−0.21)	(−0.39)	(−1.93)
BAS				−0.15***	−0.15***	−0.03
				(−3.42)	(−3.40)	(−0.48)
ME				−0.11***	−0.11***	−0.14***
				(−5.19)	(−5.11)	(−6.13)
BETA				−0.02	−0.02	−0.02
				(−0.91)	(−0.93)	(−0.54)
BM				0.18***	0.17***	0.14***
				(6.24)	(6.13)	(4.41)
MOM				−0.0002	−0.0005*	−0.0016***
				(−0.83)	(−1.77)	(−4.81)
ILLIQ				0.65***	0.64***	0.78***
				(10.58)	(10.50)	(5.84)
TURN				0.08***	0.08**	0.09**
				(2.68)	(2.57)	(2.33)
IVOL				0.07	0.07	−0.01
				(1.08)	(1.11)	(−0.18)
MAX				−0.11*	−0.11*	−0.08
				(−1.77)	(−1.76)	(−1.16)
PRC				0.02	0.02	0.06*
				(0.78)	(0.64)	(1.72)
Constant	0.17***	0.17***	0.08***	0.19***	0.19***	0.18***
	(8.15)	(8.14)	(3.47)	(9.33)	(9.38)	(6.43)

Observations	273499	273499	207597	273498	273498	207597
R^2	0.0002	0.0002	0.0386	0.002	0.0022	0.0394
Adj R^2	0.0002	0.0002	0.0386	0.0019	0.0021	0.0393
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Friday fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Abnormal returns around the same date of the previous month *before the earnings announcement*

	(1) CAR[−1,1]	(2) CAR[−1,1]	(3) CAR[−1,1]	(4) CAR[−1,1]	(5) CAR[−1,1]	(6) CAR[−1,1]
STO	0.02	0.02	0.06	0.03	0.03	0.07
	(0.69)	(0.69)	(1.60)	(0.83)	(0.83)	(1.33)
Controls			Same as Panel B			
Observations	294970	294953	220210	279910	279910	209342
R^2	0.00	0.00	0.0002	0.0003	0.0003	0.0004
Adj R^2	0.00	0.00	0.0001	0.0002	0.0002	0.0003
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Friday fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 7. Effects of earnings announcements on STO portfolio and Fama and Macbeth (1973) cross-sectional regression analyses

This table presents the effects of earnings announcement (EA) dates on decile portfolio returns and Fama and Macbeth (1973) regression results. In Panel A, we present the equal-weighted and value-weighted returns of decile portfolios sorted by STO and a 1 − 10 long-short portfolio, separately for each of the following three cases: 1) when there is an earnings announcement in month *t* (i.e., during the STO calculation month), 2) when there is an earnings announcement in month *t*+1 (i.e., during the return measurement month), and 3) when no earnings announcement occurs in months *t* and *t*+1. The columns labeled "1 − 10", "1 − 10 FF4 alpha", and "1 − 10 FF5 alpha" represent the differences between the top and the bottom STO decile portfolio in average returns, Carhart (1997) four-factor alphas, and Fama and French (2015) five-factor alphas, respectively. Panel B presents Fama and Macbeth (1973) cross-sectional regression results. Models 1-3 show the regression results when there are earnings announcements in month *t*, Models 4-6 show the results when there are earnings announcements in month *t*+1, and Models 7-9 show the results where no earnings announcements in months *t* and *t*+1. In the cross-sectional regressions, all independent variables are standardized and winsorized at the 1% and 99% levels. The numbers within parentheses indicate Newey and West (1987) corrected *t*-statistics with 12 lags. The sample period is from May 1993 to December 2022.

Panel A. Portfolio-sort analysis

	STO decile												
	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	1 − 10	1 − 10 FF4 alpha	1 − 10 FF5 alpha
Panel A1: Earnings announcement in month *t*													
Equal-	0.86	0.65	0.85	0.70	0.69	0.50	0.57	0.91	0.83	1.16	−0.30	−0.51	−0.44
weighted	(2.56)	(1.82)	(2.53)	(2.16)	(1.76)	(1.54)	(1.80)	(2.66)	(2.22)	(3.02)	(−1.24)	(−2.38)	(−1.74)
Value-	0.97	0.49	0.84	1.00	0.86	0.61	0.60	0.76	0.69	0.88	0.09	−0.29	−0.01
weighted	(3.78)	(1.80)	(2.63)	(3.49)	(2.34)	(1.91)	(1.99)	(3.18)	(2.71)	(2.83)	(0.32)	(−1.06)	(−0.02)
Panel A2: Earnings announcement in month *t*+1													
Equal-	2.12	1.52	1.35	1.35	1.32	1.26	0.95	0.95	1.04	0.86	1.26	1.17	1.25
weighted	(5.94)	(4.41)	(4.18)	(4.13)	(3.53)	(3.54)	(2.66)	(2.47)	(2.79)	(1.87)	(3.35)	(2.95)	(3.43)
Value-	1.38	1.12	1.18	1.12	1.00	1.59	1.17	0.84	0.65	0.56	0.82	0.74	0.83
weighted	(3.53)	(3.07)	(4.58)	(3.55)	(2.87)	(4.29)	(3.56)	(2.30)	(2.08)	(1.70)	(1.93)	(1.78)	(2.19)
Panel A3: No earnings announcement in months *t and t*+1													
Equal-	1.16	0.75	0.51	0.73	0.58	0.44	0.56	0.08	0.12	0.09	1.08	0.94	0.89
weighted	(2.87)	(1.84)	(1.39)	(1.98)	(1.39)	(1.19)	(1.54)	(0.22)	(0.33)	(0.25)	(6.22)	(5.39)	(5.02)
Value-	1.57	0.89	0.81	0.67	0.84	0.40	0.90	0.44	0.24	−0.14	1.71	1.48	1.77
weighted	(4.30)	(2.50)	(2.73)	(1.98)	(2.45)	(1.09)	(2.79)	(1.28)	(0.67)	(−0.44)	(6.38)	(5.23)	(6.11)

Panel B: Fama and Macbeth (1973) cross-sectional regressions

	EA in month *t*		*EA in* month *t*+1		Others	
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
STO	−0.072	−0.019	−0.245	−0.209	−0.198	−0.112
	(−1.41)	(−0.41)	(−4.29)	(−4.22)	(−4.46)	(−2.53)
RET	0.083	−0.024	−0.436	−0.407	−0.367	−0.436
	(1.43)	(−0.35)	(−4.65)	(−4.11)	(−4.38)	(−4.52)
BAS	−0.493	−0.431	−0.322	−0.238	−0.563	−0.387
	(−2.54)	(−2.43)	(−1.75)	(−1.40)	(−3.20)	(−2.16)
ME		0.010		−0.080		−0.161
		(0.13)		(−1.06)		(−1.66)
BETA		−0.063		0.069		0.070
		(−1.71)		(1.07)		(1.19)
BM		0.097		0.325		0.052
		(1.62)		(3.50)		(0.68)
MOM		0.235		0.231		0.389
		(2.36)		(2.20)		(3.56)
ILLIQ		−0.189		0.131		−0.143
		(−2.47)		(1.97)		(−2.06)
TURN		0.014		−0.016		0.034
		(0.20)		(−0.21)		(0.46)
IVOL		−0.228		−0.030		−0.290
		(−1.77)		(−0.22)		(−1.89)
MAX		0.204		−0.196		0.106
		(1.88)		(−1.27)		(0.93)
PRC		−0.144		−0.028		0.026
		(−2.10)		(−0.37)		(0.41)

Table 8. Subsample analysis

This table presents excess returns and alphas for short-term overreaction (STO) decile portfolios across different subsamples. In Panel A, we divide the sample into High- and Low- sentiment states based on the investor sentiment index from Baker and Wurgler (2006). High- (Low-) sentiment months are defined as those with an investor sentiment index above (below) the sample median for the same month in which STO is measured. In Panel B, stocks are sorted into quartiles by their level of Institutional Ownership (IO). Low and High indicate the lowest and highest IO quartiles. Similarly, in Panels C and D, stocks are sorted into quartiles by Size and Illiquidity, respectively. Low and High in Panel C and D, indicate the lowest and highest Size and Illiquidity quartile, respectively. For each subsample, at the end of each month, stocks are sorted into decile portfolios based on their STO value. We report the equal-weighted and value-weighted average returns for each STO decile portfolio. The columns labeled "1 − 10", "1 − 10 FF4 alpha", and "1 − 10 FF5 alpha" report the average returns, four-factor alphas (Carhart, 1997), and five-factor alphas (Fama and French, 2015) of the long-short portfolios that are long the highest STO decile and short the lowest STO deciles. The rows labeled "H-L" reports the difference between the High group and Low group of subsamples, for each STO decile. Parentheses indicate Newey and West (1987) corrected *t*-statistics with 12 lags. The sample period is from May 1993 to December 2022.

	STO decile											
	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	1 − 10	1 − 10 FF4 alpha	1 − 10 FF5 alpha
Panel A: Investor Sentiment													
Equal-weighted portfolio													
High	1.17	0.82	0.63	0.59	0.35	0.36	0.37	0.28	0.27	0.20	0.97	1.06	0.94
	(3.04)	(2.20)	(1.72)	(1.61)	(0.97)	(0.94)	(1.00)	(0.72)	(0.67)	(0.50)	(4.27)	(3.09)	(2.84)
Low	1.66	1.40	1.28	1.21	1.35	1.08	1.05	1.13	1.07	1.08	0.58	0.50	0.51
	(3.80)	(3.02)	(2.91)	(2.60)	(2.98)	(2.41)	(2.29)	(2.58)	(2.18)	(2.40)	(3.33)	(2.64)	(3.03)
H−L	−0.49	−0.58	−0.66	−0.62	−1.00	−0.72	−0.68	−0.84	−0.80	−0.88	0.39	0.56	0.43
	(−0.81)	(−0.91)	(−1.04)	(−0.98)	(−1.62)	(−1.18)	(−1.10)	(−1.39)	(−1.33)	(−1.57)	(1.28)	(1.94)	(1.48)
Value-weighted portfolio													
High	0.71	0.72	0.75	0.81	0.52	0.39	0.35	0.18	−0.09	−0.36	1.07	1.16	1.48
	(1.85)	(2.03)	(2.28)	(2.48)	(1.42)	(1.03)	(0.88)	(0.55)	(−0.25)	(−0.75)	(2.49)	(2.52)	(3.12)
Low	1.47	1.14	1.31	1.05	1.14	1.03	0.91	0.87	0.88	0.73	0.73	0.59	0.60
	(4.58)	(3.47)	(4.70)	(3.30)	(3.38)	(3.30)	(2.86)	(2.70)	(2.80)	(2.31)	(3.09)	(2.50)	(2.51)
H−L	−0.76	−0.42	−0.56	−0.24	−0.61	−0.64	−0.56	−0.69	−0.97	−1.09	0.33	0.56	0.87
	(−1.36)	(−0.76)	(−1.10)	(−0.48)	(−1.24)	(−1.27)	(−1.12)	(−1.39)	(−1.87)	(−2.15)	(0.75)	(1.30)	(2.04)

Panel B: Institutional Ownership

Equal-weighted portfolio													
High	1.22	1.02	1.03	1.04	0.75	0.87	0.77	0.81	0.63	0.49	0.73	0.59	0.64
	(3.83)	(3.38)	(3.47)	(3.25)	(2.63)	(2.98)	(2.54)	(2.66)	(2.16)	(1.67)	(4.03)	(2.88)	(3.28)
Low	1.16	1.00	0.48	0.44	0.30	0.17	0.08	0.17	0.24	0.36	0.80	0.86	0.74
	(4.15)	(2.91)	(1.35)	(1.22)	(0.78)	(0.44)	(0.21)	(0.46)	(0.63)	(0.97)	(3.15)	(3.00)	(2.64)
H−L	0.06	0.02	0.54	0.60	0.46	0.70	0.68	0.64	0.39	0.12	− 0.06	− 0.27	− 0.10
	(0.33)	(0.10)	(2.55)	(2.98)	(1.91)	(2.68)	(3.44)	(2.99)	(1.64)	(0.53)	(−0.22)	(−0.94)	(−0.36)
Value-weighted portfolio													
High	1.07	0.94	1.09	0.87	0.94	0.77	0.58	0.64	0.40	0.18	0.88	0.69	0.85
	(3.54)	(3.16)	(4.10)	(2.96)	(3.28)	(2.66)	(1.84)	(2.03)	(1.32)	(0.60)	(3.74)	(3.04)	(3.28)
Low	0.83	0.83	0.66	0.04	0.75	0.19	0.36	0.21	0.46	0.33	0.50	0.55	0.32
	(2.75)	(2.17)	(2.23)	(0.13)	(2.18)	(0.59)	(0.95)	(0.56)	(1.44)	(0.76)	(1.23)	(1.11)	(0.76)
H−L	0.23	0.11	0.43	0.83	0.19	0.58	0.22	0.43	−0.06	−0.14	0.38	0.14	0.53
	(0.76)	(0.38)	(1.53)	(3.57)	(0.65)	(2.56)	(0.86)	(1.32)	(−0.21)	(−0.50)	(0.87)	(0.29)	(1.25)

Panel C: Size

Equal-weighted portfolio													
High	0.94	0.99	0.90	0.92	0.89	0.78	0.73	0.65	0.63	0.55	0.39	0.24	0.39
	(3.59)	(3.65)	(3.55)	(3.61)	(3.38)	(3.02)	(2.86)	(2.18)	(2.36)	(2.14)	(2.77)	(1.57)	(2.32)
Low	1.59	1.37	1.08	0.94	0.74	0.64	0.60	0.65	0.69	0.77	0.81	0.82	0.72
	(4.59)	(3.20)	(2.65)	(2.30)	(1.74)	(1.39)	(1.38)	(1.36)	(1.58)	(1.80)	(2.97)	(2.77)	(2.44)
H−L	−0.64	−0.38	−0.18	−0.02	0.14	0.14	0.13	0.00	−0.06	−0.22	−0.42	−0.59	−0.34
	(−2.90)	(−1.33)	(−0.72)	(−0.10)	(0.50)	(0.47)	(0.47)	(0.00)	(−0.22)	(−0.77)	(−1.54)	(−2.15)	(−1.18)
Value-weighted portfolio													
High	0.96	1.07	1.02	0.85	0.80	0.72	0.63	0.58	0.44	0.28	0.69	0.57	0.69
	(3.65)	(4.07)	(4.26)	(3.31)	(2.62)	(2.73)	(2.52)	(1.99)	(1.58)	(0.89)	(2.95)	(2.41)	(2.72)
Low	1.44	1.18	1.05	0.72	0.58	0.54	0.53	0.58	0.57	0.66	0.79	0.80	0.72
	(4.56)	(3.06)	(2.72)	(1.82)	(1.48)	(1.26)	(1.21)	(1.32)	(1.41)	(1.55)	(3.04)	(2.84)	(2.57)
H−L	−0.48	−0.11	−0.02	0.14	0.22	0.18	0.10	0.00	−0.12	−0.38	−0.10	−0.23	−0.03
	(−1.99)	(−0.37)	(−0.09)	(0.47)	(0.69)	(0.58)	(0.32)	(0.01)	(−0.39)	(−1.04)	(−0.35)	(−0.84)	(−0.10)

Panel D: Illiquidity

Equal-weighted portfolio													
High	1.47	1.30	0.94	0.98	0.72	0.53	0.53	0.58	0.58	0.61	0.86	0.92	0.78
	(4.60)	(3.27)	(2.51)	(2.49)	(1.82)	(1.23)	(1.33)	(1.36)	(1.35)	(1.51)	(3.20)	(3.20)	(2.66)
Low	0.99	0.97	0.95	0.94	0.87	0.83	0.82	0.73	0.66	0.63	0.36	0.23	0.37
	(3.59)	(3.30)	(3.71)	(3.44)	(3.20)	(3.08)	(2.77)	(2.43)	(2.36)	(2.34)	(2.49)	(1.39)	(2.09)
H−L	0.48	0.33	−0.01	0.04	−0.14	−0.30	−0.29	−0.15	−0.08	−0.01	0.49	0.69	0.42
	(2.37)	(1.45)	(−0.07)	(0.18)	(−0.57)	(−1.11)	(−1.36)	(−0.60)	(−0.31)	(−0.04)	(1.74)	(2.44)	(1.34)
Value-weighted portfolio													
High	1.29	0.92	0.71	0.59	0.47	0.37	0.27	0.33	0.33	0.38	0.91	1.00	0.82
	(4.67)	(2.71)	(2.09)	(1.69)	(1.37)	(0.95)	(0.75)	(0.97)	(0.87)	(1.03)	(3.69)	(3.67)	(2.98)
Low	1.00	1.04	1.05	0.88	0.76	0.77	0.62	0.64	0.41	0.28	0.72	0.58	0.75
	(3.73)	(4.01)	(4.38)	(3.36)	(2.60)	(2.84)	(2.43)	(2.14)	(1.47)	(0.92)	(3.01)	(2.49)	(2.90)
H−L	0.29	−0.12	−0.33	−0.29	−0.29	−0.40	−0.35	−0.31	−0.08	0.10	0.19	0.42	0.07
	(1.32)	(−0.47)	(−1.32)	(−1.13)	(−1.08)	(−1.34)	(−1.39)	(−1.24)	(−0.29)	(0.32)	(0.66)	(1.54)	(0.24)

Table 9. Short and long side returns of STO portfolios

This table reports the average monthly excess returns, Carhart (1997) four-factor alphas, and Fama and French (2015) five-factor alphas for portfolios sorted by STO in Panel A and portfolios double-sorted by IO and STO in Panel B. We first sort stocks into quintiles based on STO and set quintile 3 as the neutral portfolio. The difference between quintile 3 and 5 (i.e., 3 − 5) represents the short side, and the difference between quintile 1 and 3 (i.e., 1 − 3) represents the long side of the portfolio. equal-weighted and value-weighted stand for equal-weighted and value-weighted portfolios, respectively. Panel A shows the average excess returns and alphas for STO 1 − 5 long-short portfolio returns, the short side (3 − 5), and the long side (1 − 3) of STO long-short portfolio returns. Panel B1 shows the STO 1 − 5 returns for each IO quintile. Panel B2 and B3 report the short side (3 − 5) and the long side (1 − 3) of the STO long-short portfolio returns for each IO quintile, respectively. The numbers in parentheses indicate Newey and West (1987) corrected t-statistics with 12 lags. The sample period is from May 1993 to December 2022.

Panel A: STO portfolio returns

			STO					
	1 (Low)	2	3	4	5 (High)	1 − 5	3 − 5	1 − 3
Equal-weighted portfolio								
Excess return	1.26	0.93	0.78	0.71	0.66	0.61	0.13	0.48
	(4.00)	(2.98)	(2.45)	(2.15)	(1.92)	(4.76)	(1.50)	(4.96)
FF4 alpha	0.53	0.14	0.02	−0.06	−0.03	0.56	0.04	0.51
	(3.85)	(1.71)	(0.24)	(−0.80)	(−0.26)	(3.42)	(0.47)	(4.63)
FF5 alpha	0.48	0.12	−0.02	−0.12	−0.12	0.60	0.10	0.50
	(3.66)	(1.30)	(−0.22)	(−1.50)	(−1.03)	(3.77)	(1.11)	(4.79)
Value-weighted portfolio								
Excess return	0.99	0.98	0.77	0.59	0.34	0.65	0.43	0.22
	(3.81)	(3.99)	(2.89)	(2.14)	(1.17)	(3.79)	(2.80)	(1.91)
FF4 alpha	0.23	0.21	0.05	−0.16	−0.34	0.57	0.39	0.18
	(2.54)	(2.96)	(0.99)	(−3.01)	(−2.89)	(3.27)	(2.59)	(1.50)
FF5 alpha	0.22	0.27	0.02	−0.18	−0.46	0.68	0.47	0.20
	(2.12)	(3.58)	(0.38)	(−3.48)	(−3.12)	(3.49)	(2.83)	(1.58)

Panel B: STO portfolio returns by institutional ownership

Panel B1: STO 1 − 5 for IO subsamples

				IO			
	All	1 (Low)	2	3	4	5 (High)	1 − 5
Equal-weighted portfolio (STO 1 − 5)							
Excess return	0.61	0.80	0.67	0.60	0.59	0.51	0.30
	(4.76)	(3.65)	(3.85)	(3.45)	(4.48)	(3.59)	(1.19)
FF4 alpha	0.56	0.83	0.64	0.55	0.48	0.39	0.44
	(3.42)	(3.37)	(2.92)	(2.61)	(3.18)	(2.43)	(1.79)
FF5 alpha	0.60	0.74	0.61	0.59	0.62	0.38	0.36
	(3.77)	(2.74)	(2.82)	(3.19)	(4.03)	(2.50)	(1.29)
Value-weighted portfolio (STO 1 − 5)							
Excess return	0.65	0.46	0.67	1.09	0.67	0.66	−0.21
	(3.79)	(1.62)	(3.40)	(3.90)	(3.68)	(3.56)	(−0.72)
FF4 alpha	0.57	0.40	0.63	1.06	0.56	0.52	−0.12
	(3.27)	(1.31)	(3.00)	(3.37)	(2.83)	(2.68)	(−0.44)
FF5 alpha	0.68	0.33	0.62	1.01	0.67	0.61	−0.28
	(3.49)	(1.14)	(3.16)	(3.44)	(3.20)	(2.73)	(−0.87)

Panel B2: STO 3 − 5 (short side) for IO subsamples

Equal-weighted portfolio (STO 3 − 5)							
Excess return	0.13	−0.12	0.05	0.12	0.12	0.26	−0.38
	(1.50)	(−0.74)	(0.38)	(1.08)	(1.20)	(3.21)	(−2.04)
FF4 alpha	0.04	−0.15	0.03	0.05	0.07	0.17	−0.32
	(0.47)	(−0.91)	(0.18)	(0.42)	(0.68)	(1.91)	(−1.80)
FF5 alpha	0.10	−0.14	0.03	0.12	0.18	0.14	−0.27
	(1.11)	(−0.75)	(0.20)	(1.24)	(1.77)	(1.57)	(−1.40)
Value-weighted portfolio (STO 3 − 5)							
Excess return	0.43	0.08	−0.05	0.65	0.51	0.51	−0.43
	(2.80)	(0.36)	(−0.21)	(2.84)	(3.66)	(4.26)	(−1.67)
FF4 alpha	0.39	−0.04	−0.09	0.51	0.49	0.43	−0.47
	(2.59)	(−0.18)	(−0.36)	(2.08)	(3.09)	(3.21)	(−1.86)
FF5 alpha	0.47	−0.01	−0.02	0.65	0.53	0.45	−0.46
	(2.83)	(−0.04)	(−0.07)	(2.47)	(3.41)	(3.06)	(−1.58)

Panel B3: STO 1 − 3 (long side) for IO subsamples

Equal-weighted portfolio (STO 1 − 3)							
Excess return	0.48	0.93	0.63	0.47	0.46	0.25	−0.67
	(4.96)	(5.04)	(4.77)	(3.47)	(5.06)	(2.18)	(−3.39)
FF4 alpha	0.51	0.98	0.67	0.50	0.41	0.22	−0.76
	(4.63)	(5.48)	(4.96)	(3.13)	(4.42)	(1.78)	(−3.68)
FF5 alpha	0.50	0.88	0.58	0.47	0.44	0.25	−0.63
	(4.79)	(4.79)	(4.88)	(3.13)	(4.47)	(2.11)	(−3.05)
Value-weighted portfolio (STO 1 − 3)							
Excess return	0.22	0.37	0.72	0.44	0.16	0.15	−0.22
	(1.91)	(1.38)	(2.56)	(2.16)	(1.25)	(1.06)	(−0.79)
FF4 alpha	0.18	0.44	0.72	0.54	0.07	0.09	−0.35
	(1.50)	(1.61)	(2.60)	(2.83)	(0.58)	(0.65)	(−1.28)
FF5 alpha	0.20	0.34	0.64	0.36	0.14	0.16	−0.18
	(1.58)	(1.18)	(2.29)	(1.65)	(1.09)	(1.19)	(−0.60)

Table 10. Alternative measure of STO

This table reports the average monthly excess returns, Carhart (1997) four-factor alphas, and Fama and French (2015) five-factor alphas of each decile portfolio sorted by the alternative short-term overreaction (STO) measure, constructed by daily equal weights on signed volume within month *t*. At the end of each month *t*, we group stocks into decile portfolios based on the STO over the month. We report the average returns and alphas of the decile portfolios in month *t*+1. Results are presented in both equal-weighted and value-weighted schemes. The columns labeled "1 − 10", "1 − 10 FF4 alpha", and "1 − 10 FF5 alpha" report the average returns, four-factor alphas (Carhart, 1997), and five-factor alphas (Fama and French, 2015) of the long-short portfolios that are long the highest STO decile and short the lowest STO deciles. Parentheses indicate Newey and West (1987) corrected *t*-statistics with 12 lags. The sample period is from May 1993 to December 2022.

	STO decile											
	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	1 − 10	1 − 10 FF4 alpha	1 − 10 FF5 alpha
STO, based on equal-weighted daily signed volume within the month													
Equal-	1.13	1.06	0.83	0.94	0.92	0.87	0.71	0.89	0.71	0.62	0.51	0.42	0.40
weighted	(3.53)	(3.25)	(2.65)	(3.04)	(2.86)	(2.72)	(2.22)	(2.63)	(2.14)	(1.80)	(4.28)	(2.74)	(2.56)
Value-	1.00	0.94	0.86	0.93	0.78	0.81	0.60	0.66	0.47	0.32	0.68	0.57	0.67
weighted	(3.33)	(3.41)	(3.35)	(3.64)	(3.12)	(2.92)	(2.25)	(2.43)	(1.62)	(1.04)	(2.61)	(2.14)	(2.68)