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. Contrary to most anomaly strategies, the strategy of buying low STO stocks and selling high STO stocks is more profitable when returns are value-weighted than equal-weighted. The outperformance of value-weighted portfolios is largely driven by the stronger performance of the short leg among stocks with high institutional ownership, suggesting that institutional investors may exacerbate overvaluation.

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 activity, whether driven by investor overreaction or by non-informational trades, is 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 than past return can be a better predictor of future 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 at 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 in Section 3.4 that the return predictability of our measure is likely to due to investor overreaction rather than the compensation for liquidity providers.

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 may drive 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 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. As a result, investors will be, on average, negatively (positively) surprised by subsequent earnings announcements, predicting 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 that mispricing is greater 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.

Contrary to most anomalies, our long-short STO strategy returns are consistently higher when using value-weighted returns than equal-weighted returns. When we decompose the STO strategy return into the long- and short-leg returns and examine them across subsamples formed by institutional ownership, we find that the short-leg returns of the STO strategy are higher for stocks with high institutional ownership. This is consistent with the rational speculation theory (e.g., DeLong et al. 1990, Abreu and Brunnermeir 2002, 2003) that institutions may buy overvalued stocks and ride the bubble instead of trading against mispricing. Rational speculation by institutions may explain why the STO strategy returns are higher when using value-weighted returns than equal-weighted returns.

Our study contributes to the literature on stock return predictability 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 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 investor overreaction. We construct daily signed volumes based on the assumption that high trading volume accompanied by a positive (negative) return indicates upward (downward) investor overreaction. 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 return and $VOL_{i,d}$ is the trading share volume for 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 the average weighted signed volume over the previous 12 months from $WSVOL_{i,t}$. 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.

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 use 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 composition of portfolios sorted by STO, Table 1 provides summary statistics for stocks within each decile. Panel A presents the time-series averages of the monthly cross-sectional mean values for various stock characteristics across STO deciles. Panel B shows the correlation matrix between these characteristics.

[Table 1] about here

Panel A shows that RET increases from -0.10% in the lowest STO decile to 0.16% in the highest STO decile. Additionally, MAX and TURN increase as we move from the lowest to the highest STO decile, suggesting that stocks with higher STO values experience more extreme daily returns and have higher levels of trading activities. Panel B provides a correlation matrix that offers further insights into the relationships between different stock characteristics. The correlation between STO and RET is 0.470, between STO and MAX is 0.154, and between STO and TURN is 0.024, reinforcing the findings from Panel A that stocks with higher STO values tend to have higher returns, more extreme daily returns, and higher trading activities. The correlations between STO and other characteristics, such as market capitalization (ME) and price (PRC), are close to zero.

3. Empirical analysis

3.1. Portfolio sort analysis

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

[Table 2] about here

The difference in equal-weighted excess returns between STO deciles 1 and 10 is 0.77% per month, with a 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 alpha and Fama and French (2015) five-factor alpha of the STO long-short (1 – 10) portfolio are 0.72% (*t*-stat = 3.81) and 0.73% (*t*-stat = 4.04), respectively, demonstrating economic and statistical significance. For the value-weighted portfolios, the differences in excess return, four-factor alpha, and five-factor alpha 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 highly significant for the value-weighted portfolios. Furthermore, the long-short portfolio returns are larger using value-weighted returns than equal-weighted returns.

To further investigate the relationship between short-term overreaction and future stock returns, we employ comprehensive bivariate-sort analyses that control for several well-known determinants of cross-sectional returns. These determinants include one-month return (RET), which captures the short-term return reversal, 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), share turnover (TURN), idiosyncratic volatility (IVOL), maximum daily return (MAX), and the stock price (PRC). 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 stocks with the lowest (highest) STO. Using this approach, we construct STO portfolios with comparable levels of firm size, effectively controlling for differences in size.

[Table 3] about here

Panel A of Table 3 presents the results for the equal-weighted portfolios. For brevity, we refrain from reporting returns for all 25 (5 × 5) portfolios.[2] For ease of comparison, we report the "No Control" results in the first column of Panel A, which is equivalent to the univariate-sort results where stocks are sorted into quintiles by STO. The rest of the columns of Panel A report STO

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[2] To address concerns about dependent bivariate sorts on correlated variables that may not adequately control for the control variable, we employ two approaches. First, we conduct independent bivariate sorts and find similar results (untabulated). Second, we conduct cross-sectional regressions incorporating all variables as control variables in Section 3.3.

quintile portfolio returns after controlling for each of the firm characteristics. For instance, the fourth column of Panel A Shows that, 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 STO long-short (1 – 5) differences in four-factor alphas and five-factor alphas are at 0.47% (*t*-stat = 3.22) and 0.50% (*t*-stat = 3.55) per month. When accounting for short-term reversal, bid-ask spread, beta, book-to-market ratio, momentum, illiquidity, turnover, idiosyncratic volatility, maximum daily return, and stock price, the equal-weighted average excess return difference between the low and high STO quintiles ranges from 0.44% to 0.67%, and the four- and five-factor alphas range from 0.43% to 0.65%. All differences are statistically significant.

Panel B of Table 3 reports the value-weighted excess and risk-adjusted returns of the STO portfolios while controlling for the same firm characteristics outlined in Panel A of Table 3. After controlling for each of the firm characteristics, the value-weighted average return difference between the low and high STO portfolios ranges from 0.46% to 0.68%, and the alphas range from 0.32% to 0.64%, all of which are statistically significant.

These results show that our short-term overreaction measure is a robust negative predictor of future stock returns, after controlling for the effects of several well-known determinants of cross-sectional returns such as short-term reversal, bid-ask spread, beta, book-to-market ratio, momentum, illiquidity, turnover, idiosyncratic volatility, maximum daily return, and stock price.

3.2. 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 rather than past returns can better predict future returns. Although our measure of short-term overreaction is based on trading volume, 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 0.470. While we have shown in Table 3 that the long-short STO strategy generates a significant return after controlling for RET using sequential double-sort analyses, we conduct additional analyses using independent 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. We also compare cumulative returns of long-short strategies based on STO and RET.

First, we perform four independent double-sort analyses, as shown in Table 4.

[Table 4] about here

Panel A of Table 4 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 for each STO quintile, we compute the average return across RET quintiles. This ensures that STO portfolios have similar levels of short-term return reversal. Panel A of Table 4 presents the returns of equal- and value-weighted portfolios, along with Newey and West (1987) *t*-statistics, and four-factor and five-factor alphas of the return differences between low- and high-STO portfolios.

The equal-weighted average return differences between the low and high STO portfolios (STO quintile 1 – quintile 5) have four- and five-factor alphas of 0.30% (*t*-stat = 2.70) and 0.41% (*t*-stat = 3.35), respectively. The STO 1 − 5 difference in the four-factor alphas and five-factor alphas of the value-weighted portfolios is also positive at 0.30% and 0.52% per month, with corresponding *t*-statistics of 2.00 and 2.54, respectively. Due to the high correlation between RET and STO, the return spread across the STO quintile after controlling for RET is smaller than the STO return spread in Table 3. However, short-term return reversal does not fully explain the return differences across STO quintiles.

Panel B of Table 4 assesses the explanatory power of the short-term return reversal after accounting for STO. For each RET quintile portfolio, we compute the average return across STO quintiles to control for the effect of STO. The results in Panel B reveal that when controlling for STO, the average equal-weighted excess return and alpha differences between low and high RET portfolios (RET quintile 1 – quintile 5) are positive but statistically insignificant. For value-weighted portfolios, the differences in excess and risk-adjusted returns of high and low RET portfolios are now negative after controlling for STO. However, they are all statistically insignificant.

Recent studies show that the short-term reversal effect has weakened, especially in value-weighted portfolios (e.g., Hou et al., 2014; Medhat and Schmeling, 2022; Swade et al., 2022). For instance, Hou et al. (2020) demonstrate that the long-short short-term reversal strategy delivers a significantly lower average return of 0.27% per month (*t*-stat = 1.4) when using NYSE value-weighted returns. This stands in sharp contrast to the much stronger reversal found in Jegadeesh (1990), where equal-weighted returns yielded 1.99% per month (*t*-stat = 12.55).

[Figure 1] about here

Figure 1 shows the cumulative value-weighted returns and Carhart 4-factor alphas of the STO and RET strategies. From 1993 to 2022, the cumulative long-short STO strategy produced an impressive return of 267%. In contrast, the long-short RET strategy exhibited a negative cumulative return of −154%. This stark performance divergence indicates that the STO measure captures stock misvaluation, which is distinct from short-term reversal. Figure 1 suggests that, although the short-term reversal effect has weakened in recent years, the short-term overreaction phenomenon presents a compelling case for further exploration.

In summary, we find that the long-short portfolio returns based on STO remain significantly positive after controlling for RET. In contrast, the long-short portfolio returns based on RET are insignificant and sometimes turn negative after controlling for STO, suggesting that the return predictability of one-month returns largely disappears after controlling for STO. The significant difference between the cumulative returns of the STO and RET strategies further underscores the difference between the two.

3.3. 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 using portfolio-sort analyses. While this methodology avoids imposing a specific functional form on the relation between STO and future returns, it poses a challenge because it is difficult to control for multiple factors simultaneously. Therefore, we conduct Fama and MacBeth (1973) regressions to examine the relation between STO and future returns at the individual stock level after controlling for well-known determinants of cross-sectional returns.

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

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

where $ret_{i,t+1}$ is the return on stock i in month t+1, and $STO_{i,t}$ is the 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), share turnover (TURN), idiosyncratic volatility (IVOL), maximum daily return (MAX), and the stock price (PRC). The independent variables are winsorized at the 1% and 99% levels, and then standardized.

[Table 5] about here

Table 5 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 results in Model 1 indicate a significant and negative association between STO and future stock returns, confirming our earlier results that upward (downward) short-term overreaction predicts lower (higher) future returns. The average slope $\lambda_{1,t}$ is −0.254, with a corresponding *t*-statistic of −6.67. The coefficient indicates that a shift in STO value from a 1.65 standard deviation below the mean to a 1.65 standard deviation above the mean, which spans 90% of a normal distribution, leads to a 0.838% decrease in expected returns. This economic impact is in line with the results shown in Table 2, where stocks in the top decile of STO have expected returns that are 0.77% lower than those in the bottom decile.

When we add short-term reversal (RET) in Model 2, we find that STO remains highly significant while RET has an insignificant effect. The results of Model 2 corroborate the results in Table 4 that the return predictive power of STO is not subsumed by that of short-term reversal (RET), while short-term return reversal loses its power when STO is included. Model 3 of Table 5 reports the results when the control variables are included. 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.

Previous literature has shown that the return predictability of past returns is influenced by trading volume. Medhat and Schmeling (2022) show 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) find that an increase in the number of transactions is associated with greater return reversal in weekly returns. Cooper (1999) reports a weaker reversal in weekly returns among stocks with higher growth in trading volume. Avramov et al. (2006) show that higher turnover corresponds to a stronger reversal in weekly returns but a weaker reversal in monthly returns.

According to this body of literature, the return predictive power of short-term return depends on the level of trading volume. This indicates that the interaction term between one-month return (RET) and share turnover (TURN) may have significant predictive power for future returns. Although we have shown that STO remains a significant predictor of future return after controlling for RET, one may argue that the predictive power of STO might disappear once we account for the interaction between one-month return (RET) and share turnover (TURN).

To address this concern, Models 4 and 5 in Table 5 include both TURN and the interaction term RET×TURN in the cross-sectional regression analysis, with and without control variables. Following Medhat and Schmeling (2022), we define TURN as the number of shares traded in the month divided by the total number of shares outstanding. Even with this additional set of controls, the predictive power of STO remains significant. For instance, Model 5 in Table 5 shows that the coefficient of STO remains significant, with a value of −0.099 (t-stat= −3.63), after controlling for the interaction between RET and TURN along with all other control variables. The interaction term RET×TURN is positive, indicating weaker return reversal among high turnover stocks, consistent with Avramov et al. (2006) and Medhat and Schmeling (2022).

In summary, the results in Table 5 suggest that STO is a strong return predictor after controlling for known determinants of cross-sectional returns, as well as the short-term return reversal and its interaction with trading volume.

3.4. Stock price reactions to subsequent earnings announcements

So far, we have assumed that our STO measure is a proxy for 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 may be driven by investor overreaction and/or 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 absorbing 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 abnormal returns around the subsequent earnings announcement date should not differ from the relation between STO and 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 the earnings announcement date. The independent variables include $STO_{i,t}$ 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 stock price 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 support our overreaction story rather than the liquidity provision story. The results suggest that STO captures investors' short-term overreaction, and that the return predictability of STO is driven by the subsequent correction of the 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 that is subsequently corrected, especially when there are public information announcements such as earnings announcements. This implies that the timing of the arrival of public information 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 STO long-short (1 − 10) 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 in the STO measurement month (month *t*).

If investors' short-term overreaction as measured by STO is partially corrected when there is an earnings announcement, as shown in Table 6, it is possible that STO calculated in the earnings announcement month captures the correction in response to public information rather than the overreaction. This may explain why STO loses its return predictability when there is an earnings announcement in the STO measurement month. It is also possible that STO captures investor reactions to public information (earnings news) when there is an earnings announcement in 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 investor overreaction is largely driven by the overreaction to intangible information rather than the overreaction to tangible (public) information.

4. Additional analysis

4.1. Subsample analysis

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

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

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 STO long-short (1 – 10) portfolio returns are 1.16% and 1.48%, respectively, in high-sentiment months, while they are 0.59% and 0.60%, respectively, in low sentiment months. The difference between the high and low sentiment months is more pronounced in the short leg (STO decile 10) of the long-short portfolio. 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 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 ownership and low institutional ownership stocks in the profitability of the STO strategy. For instance, the five-factor alpha of the equal-weighted STO long-short (1 – 10) 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. Moreover, STO portfolio returns of the subsamples split by firm size and by illiquidity suggest that the long-short

STO strategy profits are larger for small and illiquid firms but the differences between the subsamples are mostly insignificant. 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, the magnitude and significance of the 4-factor and 5-factor alphas indicate that the long leg (STO decile 1) outperforms the short leg in equal-weighted returns, while the short leg (STO decile 10) outperforms the long leg in value-weighted returns.

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

[Table 9] about here

Panel A of Table 9 provides the excess returns and the alphas 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 STO long leg (1 − 3) return is 0.48% with a t-statistic of 4.96, compared to the STO short leg (3 − 5) return of 0.13% with a t-statistic of 1.50. Conversely, the STO short leg (3 − 5) of the value-weighted portfolios shows a stronger performance than the long leg, posting a return of 0.43% with a t-statistic of 2.80, while the STO long leg (1 − 3) return of 0.22% with a *t*-statistic of 1.91.

To gain insight into the disparate patterns of equal-weighted and value-weighted returns in the long and short legs of the STO strategy, we examine the results by institutional ownership (IO) subsamples in Panel B of Table 9. This panel reports the STO long-short (1 − 5) portfolio return as well as the long and short leg returns for each IO quintile. Panel B1 shows that the equal-weighted STO long-short (1 − 5) returns 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 STO long-short (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 STO long-short (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 STO short leg (3 − 5) returns increase from low to high IO. Particularly, the value-weighted STO short leg return is significantly positive in high IO, contributing to the overall strength of the value-weighted returns of the STO strategy. For instance, the value-weighted STO short leg (3 − 5) return is 0.51% (*t*-stat = 4.26) in high IO (IO quintile 5), 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. However, the results 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, which is consistent 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 STO long leg (1 − 3) returns are stronger among low IO stocks, particularly for equal-weighted returns. For example, the equal-weighted STO long leg (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 a stronger performance of the STO strategy among high IO stocks. In contrast, the long leg (negative overreaction) return is related 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 for value-weighted returns than for equal-weighted returns.

4.3. Robustness Tests

In this section, we perform robustness tests by examining whether the observed return predictive power of STO is sensitive to the effect of microcap stocks or to the weighting method in the construction of STO. Some studies categorize microcaps as stocks with a market value below the 20th percentile of NYSE stocks (e.g., Fama and French, 2008, Hou et al., 2020). Hou et al. (2020) show that some anomalies, including the short-term return reversal (Jegadeesh 1990), disappear when microcap stocks are excluded. We re-examine the STO decile portfolio returns after excluding stocks with market capitalizations below the NYSE 20th percentile to ensure that our results are not driven by microcap stocks.

We also construct an alternative STO measure in which daily signed volume is equally weighted (i.e., W_d set to $1/D$ in Equation (2) of Section 2.1), in contrast to the original STO measure that uses higher weights towards the end of the month. We use an increasing weight towards the end of the month in the original STO measure to identify the trend of short-term overreaction. The trend plays an important role in predicting the next month's return, because stocks that are likely to be at the peak of short-term overreaction at the end of month *t* are likely to have lower returns in month $t+1$, compared to those that are already in the correction phase of short-term overreaction in month *t*. Nevertheless, we examine how sensitive our results are to the weighting method.

[Table 10] about here

Table 10 shows the results of robustness tests using three specifications. Panel A reports the STO decile portfolio returns after excluding the microcap stocks. The equal-weighted (value-weighted) average of the excess return difference between deciles 1 and 10 is 0.65% (0.94%) per month, with the Newey and West (1987) *t*-statistic of 4.65 (3.57). The four- and five-factor alphas are 0.53% (*t*-stat = 3.13) and 0.65% (*t*-stat = 3.81) for equal-weighted portfolios, and 0.81% (*t*-stat = 3.24) and 0.98% (*t*-stat = 3.68) for value-weighted portfolios. The results show that the predictive power of STO is highly significant even after excluding microcap stocks. This provides further evidence that the return predictability of STO is distinct from the short-term return reversal, which is mainly driven by microcap stocks.

Panel B reports the returns of the decile portfolios formed by the alternative STO measure based on the equal-weighted average of daily signed volume. We find that the results using the alternative STO measure are qualitatively similar to the results using the original STO in Table 2, but smaller in magnitude. This is not surprising, as an increasing weighting scheme used for the original STO should better capture the trend of short-term overreaction and have stronger return predictive power. Similar to the results using the original STO, the average returns decrease almost linearly as the alternative STO decile increases. The equal-weighted average of the excess return difference between deciles 1 and 10 is 0.51% (*t*-stat = 4.28) per month, and the four-factor and five-factor alphas are 0.42% (*t*-stat = 2.74) and 0.40% (*t*-stat = 2.56), respectively. The results are stronger when we use value-weighted returns, with the four-factor alpha of 0.57% (*t*-stat = 2.14) and the five-factor alpha of 0.67% (*t*-stat = 2.68) for the long-short portfolio using deciles 1 and 10. Panel C reports the alternative STO decile portfolio returns after excluding the microcap stocks. The value-weighted return, four-factor alpha, and five-factor alpha differences between the highest and lowest alternative STO decile portfolios are 0.69% (*t*-stat = 3.26), 0.59% (*t*-stat = 2.96), and 0.70% (*t*-stat = 3.57), respectively.

In summary, the results in Table 10 suggest that our results are robust to the exclusion of microcap stocks or to the use of the equal-weighted average of daily signed volumes in constructing STO measure. The results also provide additional evidence that the return predictability of our STO measure is distinct from the short-term return reversal, which loses its power when microcap stocks are excluded.

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 that exhibit 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 the 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 show 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. We also find that the short leg returns of the STO strategy are higher for stocks with high institutional ownership, which is consistent with the rational speculation theory and may explain why our STO strategy returns are higher when using value-weighted returns than equal-weighted returns. The return predictability of STO remains significant after controlling for the interaction effects of turnover and the past one-month return and after excluding microcap stocks, providing further evidence that the STO effect is distinct from the short-term reversal.

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. It may also have broader implications for other anomalies that are related to investor overreaction.

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Appendix. Variable Descriptions

Table A. Variable Descriptions

$STO_{i,t}$	$STO_{i,t}$ is the short-term overreaction measure of stock *i* in month *t*. We first calculate the daily signed volume for stock *i* in day *d*, defined as follows: $$SVOL_{i,d} = \begin{cases} VOL_{i,d} & \text{if } ret_{i,d} > 0 \\ 0 & \text{if } ret_{i,d} = 0 \\ -VOL_{i,d} & \text{if } ret_{i,d} < 0 \end{cases}$$ where $ret_{i,d}$ is the return and $VOL_{i,d}$ is the trading share volume for stock *i* in day *d*. Then, we define the weighted signed volume of stock *i* in month *t* ($WSVOL_{i,t}$) as the sum of daily weighted signed volumes divided by the average daily trading volume during the month: $$WSVOL_{i,t} = \frac{\sum_{d=1}^{D} SVOL_{i,d} \times W_d}{VOL_{i,t}}$$ where $SVOL_{i,d}$ is the signed daily volume 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 $d = 1, 2, \ldots, D$). $STO_{i,t}$ is the difference between $WSVOL_{i,t}$ and the average $WSVOL_{i,t}$ over the previous 12 months.
$RET_{i,t}$	$RET_{i,t}$ is the return of stock *i* in month *t*.
$BAS_{i,t}$	$BAS_{i,t}$ is the monthly average of daily bid-ask spread, defined as bid price minus ask price, divided by the midpoint price. The midpoint price is calculated as the best available average price between the ask and bid prices.
$BM_{i,t}$	$BM_{i,t}$ is the natural logarithm of the firm's book-to-market ratio from the most recent fiscal year ending at least six months prior to month *t*, following Fama and French (1992).
$ME_{i,t}$	$ME_{i,t}$ is the natural logarithm of stock *i*'s market capitalization defined as the total number of shares outstanding for firm *i* multiplied by the share price on the last day of month *t*, 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 during month *t*, 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 market return, calculated as the value-weight return of all NYSE, AMEX, and NASDAQ stocks minus the Treasury bill rate for days *d-1, d,* and *d+1,* respectively. *BETA* of stock *i* at the end of the month *t* is calculated as $\widehat{\beta_{1,i}} + \widehat{\beta_{2,i}} + \widehat{\beta_{3,i}}$.

$IVOL_{i,t}$	$IVOL_{i,t}$ is the standard deviation of the residuals from the Fama and French (1993) three-factor model, estimated using daily returns for month *t*, 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* in month *t* is defined as the standard deviation of the residuals, $\epsilon_{i,d}$, in month *t*.
$ILLIQ_{i,t}$	$ILLIQ_{i,t}$ is the illiquidity measure of stock *i* in month *t*., following Amihud (2002). The equation is 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 share turnover of stock *i* in month *t*, 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 of stock *i* in month *t*, defined as the number of shares held by institutional investors in the most recent quarter preceding month *t* divided by the total number of shares outstanding.
$MAX_{i,t}$	$MAX_{i,t}$ is the maximum daily return of stock *i* 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*.
$CAR[-1,1]_{i,t}$	$CAR[-1,1]_{i,t}$ is the size-adjusted cumulative abnormal return of stock *i* over days [-1,1] around the event date (e.g., earnings announcement date) in month *t*. $CAR[-1,1]_{i,t}$ is computed as the difference between the 3-day compounded returns of the stock *i* and the 3-day compounded value-weighted returns of the size quintile to which the stock belongs to: $$CAR[-1,1]_{i,t} = \prod_{j=-1}^{1}(1 + ret_{i,j}) - \prod_{j=-1}^{1}(1 + Sret_{k,j}),$$ where $ret_{i,j}$ is the return of stock *i*, $Sret_{i,j}$ is the value-weighted return of the size portfolio *k* to which stock *i* belongs to.
$SUE_{i,t}$	$SUE_{i,t}$ is the earnings surprise of stock *i* for earnings announcement in month *t*, following Livnat and Medenhall (2006). $SUE_{i,t}$ is calculated as the difference between the reported earnings per share (EPS) and the median of analyst earnings forecasts reported within the 90 days prior to the earnings announcement, both obtained from I/B/E/S. This difference is then divided by the stock price at the end of the quarter.

Figure 1. Cumulative value-weighted returns and Carhart (1997) four-factor alphas for long-short STO and RET strategies

This figure presents the cumulative value-weighted returns and Carhart (1997) four-factor alphas for the long-short portfolios based on the short-term overreaction (STO) and short-term return reversal (RET). The long-short STO portfolio is constructed by taking a long position in the bottom decile and a short position in the top decile based on the STO measure at the end of each month and hold the position for one month. The long-short RET portfolio follows the same methodology but uses the RET measure. The solid (dashed) lines represent the cumulative returns and alphas for long-short STO (RET) portfolios. The sample period spans from January 1993 to December 2022.

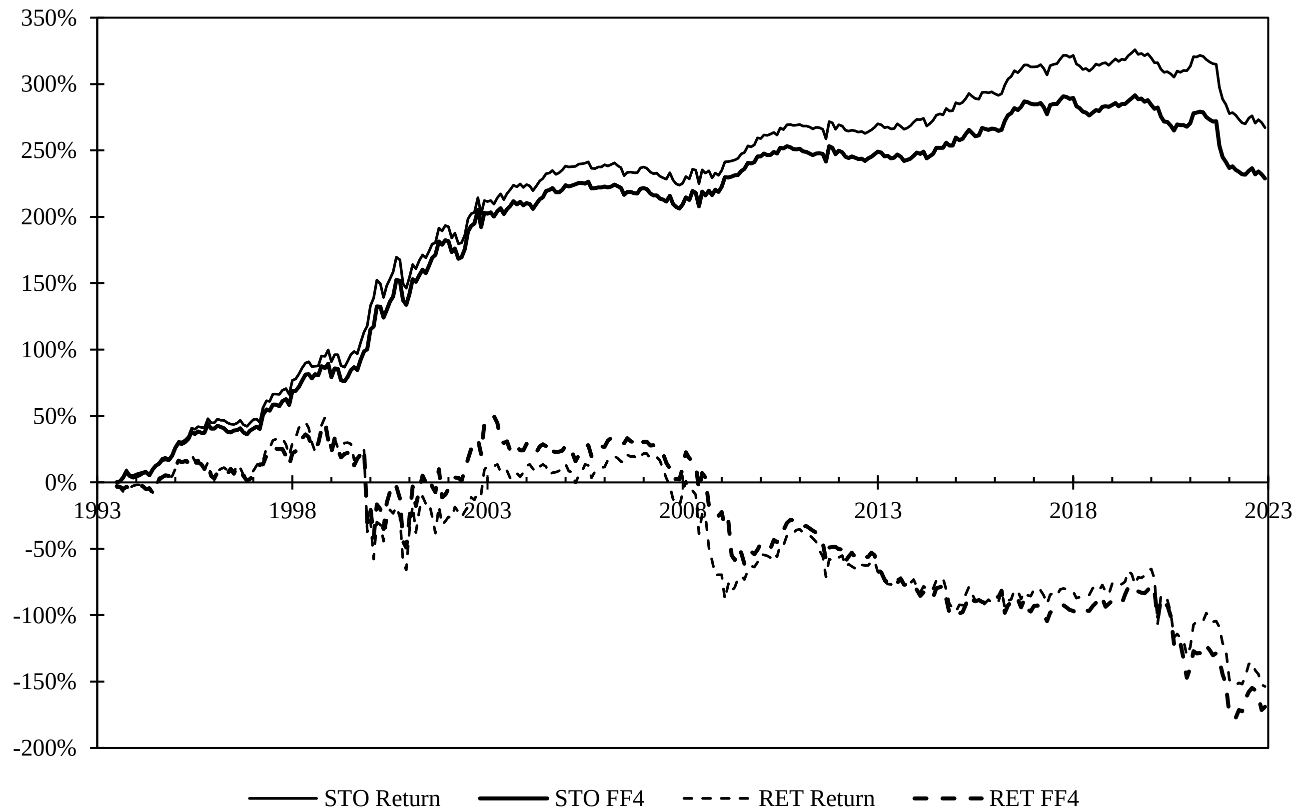

Table 1. Summary statistics

This table reports the average stock characteristics for STO (short-term overreaction) decile portfolios. Panel A reports the time-series averages of the monthly cross-sectional mean 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), share 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 the variables in Panel A. The variable definitions are provided in the 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	0.470	1										
BAS	0.036	0.078	1									
ME	-0.001	0.005	-0.145	1								
BETA	-0.023	-0.011	0.131	0.005	1							
BM	0.012	0.022	0.074	-0.079	-0.048	1						
MOM	-0.114	-0.009	-0.072	0.022	0.027	0.021	1					
ILLIQ	0.003	0.001	0.179	-0.027	-0.051	0.097	-0.048	1				
TURN	0.024	0.126	0.285	-0.005	0.134	-0.079	0.097	-0.064	1			
IVOL	0.072	0.211	0.773	-0.124	0.064	0.084	-0.081	0.189	0.330	1		
MAX	0.154	0.403	0.622	-0.086	0.086	0.059	-0.073	0.140	0.324	0.894	1	
PRC	-0.000	0.006	-0.064	0.175	-0.004	-0.026	0.020	-0.009	-0.011	-0.046	-0.032	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 (in percentages) of decile portfolios 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 in month t and compute the returns of each portfolio in month t+1. Panel A (B) reports the average excess returns and alphas of equal-weighted (value-weighted) portfolios. The column labeled "1 − 10" represents the difference between the bottom and the top STO decile portfolios. The numbers in parentheses are 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
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 reports the average monthly excess returns and risk-adjusted alphas (in percentages) using the dependent bivariate-sort methodology based on the short-term overreaction (STO) measure after controlling for each of the following variables: 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), share 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 into quintiles based on STO. Panel A (B) reports the equal-weighted (value-weighted) returns of STO quintile portfolios, calculated by averaging the returns of the five portfolios within each STO quintile (e.g., average of RET quintiles 1,2,3,4, and 5 within each STO quintile). The row labeled "1 − 5," "1 − 5 FF4 alpha," and "1 − 5 FF5 alpha" represent the difference in excess returns, Carhart (1997) four-factor alphas, and Fama and French (2015) five-factor alphas between STO quintile 1 and quintile 5. The numbers in parentheses are 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. Bivariate-sort analysis of STO and RET

This table reports the average monthly excess returns and risk-adjusted alphas (in percentages) of the 25 portfolios formed by independent double-sort based on the short-term overreaction (STO) measure and short-term return reversal (RET). In Panel A (B), the row "Average" is the average value of portfolio excess returns for each STO (RET) quintile. The columns labeled "1 − 5," "1 − 5 FF4 alpha," and "1 − 5 FF5 alpha" represent differences between STO (RET) quintile 1 and quintile 5 in excess returns, Carhart (1997) four-factor alphas, and Fama and French (2015) five-factor alphas. Results are presented in both equal-weighted and value-weighted schemes. The numbers in parentheses are 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 5. Fama and MacBeth (1973) cross-sectional regressions

This table reports the results of the Fama and MacBeth (1973) cross-sectional regression. We report the time-series averages of the regression coefficients from monthly regression of the return on stock *i* in month *t*+1 on our short-term overreaction measure, STO, and control variables. Control variables include short-term return reversal (RET), share 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), the stock price (PRC), and the interaction term of RET and TURN (RET×TURN). The independent variables are winsorized at the 1% and 99% levels and then standardized. The numbers in parentheses are Newey and West (1987) corrected *t*-statistics with 12 lags. The variable definitions are provided in the Appendix. The sample period is from May 1993 to December 2022.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
STO	−0.254	−0.220	−0.116	−0.211	−0.099
	(−6.67)	(−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			−0.296		−0.298
			(−1.81)		(−1.93)
ME			−0.079		−0.068
			(−1.40)		(−1.22)
BETA			0.014		0.012
			(0.48)		(0.43)
BM			0.133		0.142
			(1.69)		(1.81)
MOM			0.283		0.278
			(3.19)		(3.28)
ILLIQ			−0.042		−0.035
			(−1.03)		(−0.86)
IVOL			−0.161		−0.137
			(−2.00)		(−1.66)
MAX			−0.063		−0.050
			(−0.78)		(−0.63)
PRC			−0.080		−0.090
			(−1.50)		(−1.68)

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 (in percentages) over the event window [−1,1] of the earnings announcement date. The independent variables include the standardized unexpected earnings (SUE), the prior quarter's earnings announcement 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), share 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 as the earnings announcement date as the dependent variable. All independent variables are winsorized at the 1% and 99% levels and then standardized. 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)

	(1)	(2)	(3)	(4)	(5)	(6)
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)	(2)	(3)	(4)	(5)	(6)
	CAR[−1,1]	CAR[−1,1]	CAR[−1,1]	CAR[−1,1]	CAR[−1,1]	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 reports the effects of earnings announcement (EA) dates on STO decile portfolio returns and Fama and MacBeth (1973) regression results. In Panel A, we present the equal- and value-weighted returns and risk-adjusted alphas (in percentages) of decile portfolios and 1 − 10 long-short portfolio sorted by STO, 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 average returns, Carhart (1997) four-factor alphas, and Fama and French (2015) five-factor alphas of the long-short portfolios that are long the lowest STO decile and short the highest STO decile. Panel B presents Fama and MacBeth (1973) cross-sectional regression results. Models 1and 2 show the regression results when there are earnings announcements in month t, Models 3 and 4 show the results when there are earnings announcements in month t+1, and Models 5 and 6 show the results where there are no earnings announcements in months t and t+1. In the cross-sectional regressions, all independent variables are winsorized at the 1% and 99% levels and then standardized. The numbers in parentheses are 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		No EA in months *t* and *t+1*	
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 reports the average monthly excess returns and risk-adjusted alphas (in percentages) of 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 month in which STO is measured. In Panel B, stocks are sorted into quartiles by their level of Institutional Ownership (IO). The rows labeled "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. The rows labeled "Small" and "Large" in Panel C and "Low" and "High" in Panel 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. 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 lowest STO decile and short the highest STO decile. The rows labeled "High-Low" ("Big-Small") report the differences between the subsamples for each STO decile. The numbers in parentheses are 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)
High−Low	−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)
High−Low	−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)

	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 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)
High−Low	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)
High−Low	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													
Big	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)
Small	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)
Big−Small	−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													
Big	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)
Small	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)
Big−Small	−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)

	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 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)
High−Low	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)
High−Low	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 (in percentages) of 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 quintiles 3 and 5 (i.e., 3 − 5) represents the short side, and the difference between quintiles 1 and 3 (i.e., 1 − 3) represents the long side of the STO strategy. Results are presented in both equal-weighted and value-weighted schemes. Panel A shows the average returns and alphas for the STO long-short (1 – 5) portfolio, STO short leg (3 − 5), and STO long leg (1 − 3). Panel B1 shows the STO long-short (1 – 5) portfolio returns for each IO quintile. Panel B2 and B3 report the returns and alphas of the STO short leg (3 − 5) and the STO long leg (1 − 3) for each IO quintile, respectively. The numbers in parentheses are 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			Long-Short	Short leg	Long leg
	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 long-short (1 – 5) for IO subsamples

				IO			
	All	1 (Low)	2	3	4	5 (High)	*IO* 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 short leg (3 − 5) for IO subsamples

				IO			
	All	1 (Low)	2	3	4	5 (High)	*IO* 1 − 5
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 long leg (1 − 3) for IO subsamples

				IO			
	All	1 (Low)	2	3	4	5 (High)	*IO* 1 − 5
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. Robustness Tests

Panel A reports the STO portfolio sort analysis results, excluding microcap stocks (defined as firms below the 20th percentile of NYSE market capitalization). Panels B and C report the results of portfolio sort analysis using an alternative STO measure, which is calculated based on daily equal-weighted signed volumes within each month. Panel B includes all stocks, while Panel C excludes microcap stocks. We report the average monthly excess returns, Carhart (1997) four-factor alphas, and Fama and French (2015) five-factor alphas (in percentages) of the STO decile portfolios. 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 lowest STO decile and short the highest STO decile. The numbers in parentheses are 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. STO portfolio returns, excluding microcap stocks													
Equal-	1.23	0.99	0.92	0.98	0.85	0.81	0.76	0.80	0.75	0.58	0.65	0.53	0.65
weighted	(4.18)	(3.38)	(3.39)	(3.35)	(2.92)	(2.87)	(2.51)	(2.65)	(2.50)	(1.99)	(4.65)	(3.13)	(3.81)
Value-	1.12	0.88	1.08	0.92	0.82	0.68	0.70	0.57	0.43	0.18	0.94	0.81	0.98
weighted	(4.17)	(3.40)	(4.33)	(3.59)	(2.86)	(2.59)	(2.43)	(2.01)	(1.56)	(0.55)	(3.57)	(3.24)	(3.68)
Panel B. Alternative STO portfolio returns													
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)
Panel C. Alternative STO portfolio returns, excluding microcap stocks													
Equal-	1.06	0.94	0.86	0.90	0.92	0.88	0.82	0.86	0.74	0.67	0.39	0.25	0.30
weighted	(3.42)	(3.20)	(3.05)	(3.26)	(3.14)	(3.03)	(2.87)	(2.95)	(2.55)	(2.29)	(2.84)	(1.62)	(1.78)
Value-	0.93	0.91	0.95	0.86	0.81	0.81	0.70	0.56	0.54	0.24	0.69	0.59	0.70
weighted	(3.18)	(3.42)	(3.76)	(3.31)	(3.30)	(3.04)	(2.47)	(2.01)	(1.85)	(0.81)	(3.29)	(2.96)	(3.57)