

# Reference-Dependency of Short-Term Reversal

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## Abstract

The short-term reversal anomaly is believed to be the compensation for the liquidity provision. We put forth the hypotheses that i) liquidity provision for a stock increases with capital gains overhang of the stock and ii) the short-term reversal of a stock becomes more pronounced when shareholders in aggregate have a large capital loss overhang in that stock. Our empirical findings support our hypotheses, and the results stand firmly even after controlling for risk as well as lottery preference and past return effects that are known to be determinants of short-term reversals.

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# 1. Introduction

The negative serial correlation of individual stock's monthly returns, which is documented first by Jegadeesh (1990), is one of the most interesting anomalies that are not fully explained. The leading explanation for the short-term reversal anomaly is the compensation for liquidity provision (Kaniel, Sarr, and Titman, 2008; Nagel, 2012; Cheng, Hameed, Subrahmanyam, and Titman, 2017). When there is a liquidity shock, for example, liquidity providers will take the opposite side of orders and require compensation in return. For example, if there is a sudden and temporary increase in buy orders, liquidity providers take the short side at a price higher than the fundamental value. This higher price will converge to the fundamental value subsequently, and we will observe a return reversal in this process.

This paper studies the influence of behavioral biases to the liquidity provision and provides empirical evidence regarding how this behavioral bias may affect the short-term reversal anomaly. Based on the previous literature showing that the short-term return reversal is mainly due to the compensation for liquidity provision, the factors affecting liquidity provision will influence the short-term return reversal. It is widely believed that individual investors are exposed to behavioral biases (See Barberis and Thaler, 2005), and Kaniel et al. (2008) document that individual investors are liquidity providers. Thus, we can hypothesize that liquidity provision depends on the behavioral biases affecting individual investors.

Empirical evidence shows that in the stock market, investors tend to sell stocks with paper gain too early and hold stocks too long with paper loss, which is the phenomenon called the disposition effect (Shefrin and Statman, 1985; Grinblatt and Han, 2005; Frazzini, 2006). Like many other well-known behavior biases, this disposition effect is believed to appear more strongly among individual investors. (Odean, 1998; Grinblatt and Keloharju, 2001; Chang, Solomon, and Westerfield, 2016). In this study, based on the existing literature showing that individual investors are liquidity providers and they are more affected by the disposition effect, we argue that liquidity providers are more influenced by the disposition effect than other investors. Moreover, liquidity providers are affected by the disposition

effect when they are on the selling side. The disposition effect is caused by the selling pressure from investors with capital gains overhang.

Our first hypothesis is that liquidity provision depends on capital gains overhang especially for stocks experiencing buying pressure. Because investors are more willing to sell their stocks with large capital gains overhang, they are more willing to provide liquidity when the other investors want to buy. On the other hand, capital gains overhang is not related to the tendency to buy and thus it will not affect liquidity provision when the market wants to sell. If our first hypothesis is correct, the asymmetric dependence of liquidity provision will lead the asymmetric short-term reversal. Among the stocks with large (small) capital gains overhang, liquidity providers will provide liquidity more (less), thus reducing (enhancing) the compensation for providing liquidity. Thus, our second hypothesis is that the short-term reversal effect is stronger in stocks with large aggregate capital losses.

To test our hypotheses, we use the US stock market data and construct a proxy for capital gains overhang in an individual stock level following the method suggested by Grinblatt and Han (2005). Our results confirm the two hypotheses. By employing abnormal turnover measure and the price impact measure of Amihud (2002) as proxies to estimate liquidity, we confirm the asymmetric relationship between liquidity and capital gains overhang. Stocks with large capital gains overhang are more liquid and they are especially so when stocks are experiencing buying pressure. In more details, we employ liquidity variables as dependent variables, and include the interaction term between capital gains overhang and past one month return with various control variables as independent variables and find the presence of the asymmetric relationship between capital gains overhang and liquidity.

Capital gains overhang also plays a critical role in the size of short-term reversal anomaly. The short-term reversal anomaly is pronounced with the stocks with large unrealized losses. In particular, among stocks with large paper losses, the underperformance of winner stocks compared to loser stocks is 1.41% per month, which is more than 3 times higher in magnitude compared to stocks with large paper gains. The magnitude of difference in anomalous return is statistically significant and economically

meaningful, and does not vanish after controlling for previously known risk factors. The Fama-Macbeth (1973) regression gives a similar result. In net of other control variables, the negative serial correlation of monthly stock returns is strengthened among stocks with large unrealized gains.

Overall, our empirical results indicate that capital gains overhang plays a critical role in determining the magnitude of liquidity provision and short-term reversal. However, there may be other explanations. For example, this might be due to investors' preference to lottery-like stocks. Bali, Cakici, and Whitelaw (2011) document that investors prefer and overvalue lottery-like stocks and thus there is underperformance among lottery-like stocks. Because overvalued lottery-like stocks are more likely to enjoy positive previous returns, this underperformance of lottery-like stocks may appear as short-term reversals. An, Wang, and Wang (2017) document that the underperformance of lottery-like stocks is reference-dependent and it appears mostly among stocks with small capital gains overhang while it becomes insignificant among stocks with large capital gains overhang. Thus, it is possible that our results are driven by the lottery-like features of our winners. Another possible explanation is the finding of Cheng et al. (2017), who find that the magnitude of short-term reversal anomaly is larger for loser stocks in the previous quarter. They argue that the short-term reversal anomaly is stronger among stocks experiencing a recent drop because of the outflow of liquidity providers. Because past stock return performance is highly correlated to the capital gains overhang, there is a possibility that our result is just another representation of their empirical findings. We confirm that our results stand firmly even after controlling for these two effects.

Our contributions to the literature can be summarized as follows. First, the existing literature has extensively documented that the short-term return reversal is the compensation for liquidity provision. Our results confirm the importance of liquidity provision in explaining the short-term return reversal by showing that capital gains overhang affects the short-term reversal through the liquidity provision channel. Second, our empirical findings not only confirm the existing liquidity provision hypothesis but also show when the short-term reversal is strengthened. Cheng et al. (2017) document that the short-

term reversal becomes stronger for stocks that were losers in the previous quarter. We document that CGO is another important factor affecting the magnitude of the short-reversal. Third, our paper also contributes to the literature on the reference-dependent preference. Recently, it is known that the risk-return relationship or lottery-preference is reference-dependent (Wang, Yan, and Yu, 2016; An et al., 2017). Our findings suggest that the magnitude of short-term reversal anomaly heavily depends on the capital gains overhang. In other words, the reference price affects the liquidity provision behavior and as a result, short-term reversal.

The remainder of the paper is organized as follows. Section 2 demonstrates our hypotheses. In Section 3, our data and methodology are described. Section 4 represents our empirical result and Section 5 concludes

## **2. Hypotheses**

In this section, we provide a possible reason about why the reference-dependence of the short-term reversal anomaly exists and put forth hypotheses. We argue that the selling pressure difference, which is induced by individual investors' capital gains overhang, is the main reason for the existence of this anomalous phenomenon.

It is known in the literature that there exists the so-called disposition effect; shareholders prefer to realize gains over losses. This implies that the pressure to realize profits increases the selling pressure of stocks with large unrealized gains. In other words, stocks with paper gains will have higher selling pressure compared to those with paper losses. This disposition effect is believed to appear more strongly among individual investors. They are unsophisticated and thus more likely to possess and show the behavioral bias.

On the other hand, Kaniel et al. (2008) document that individuals generally tend to take contrarian

strategies in a short term; individuals tend to sell stocks experiencing a recent rise in prices and buy stocks experiencing a recent decline in prices. They interpret these results as evidence showing that individual investors, in aggregate, participate as liquidity providers in the stock market.

In this study, based on the existing literature showing that individual investors are liquidity providers and they are more affected by the disposition effect, we argue that liquidity providers are more influenced by the disposition effect than other investors. Moreover, liquidity providers are affected by the disposition effect when they are on the selling side. The disposition effect is caused by the selling pressure from investors with capital gains overhang.

According to the framework of the disposition effect, investors are more willing to sell their stocks with large capital gains overhang. Moreover, our argument implies that liquidity providers are more affected by the disposition effect compared to other investors. Consequently, liquidity providers are more willing to provide liquidity in stocks with large capital gains overhang when the other investors want to buy. On the other hand, capital gains overhang is not related to the tendency to buy and thus it will not affect liquidity provision when the market wants to sell. As a result, liquidity provision increases with buying pressure when liquidity providers are in the state of paper gains. Thus, we put forth the following hypothesis:

**Hypothesis 1.** Liquidity provision increases with capital gains overhang especially for stocks experiencing buying pressure.

It is widely accepted that the short-term reversal anomaly is mainly caused by the compensation for liquidity provision. If there is a positive demand shock to a stock, it takes up the liquidity in the market and thus the compensation for the liquidity provision will go up. As a result, the price goes up temporarily and then it will return to the normal price later. In this framework, the compensation for liquidity provision increases when there is less liquidity provision. Because individual investors are liquidity providers and they are more likely to provide liquidity when they have more paper gains for the stock, liquidity provision is affected mainly by the amount of capital gains overhang. This implies

that the compensation for liquidity provision increases (decreases) with capital losses (gains) overhang and thus the short-term reversal anomaly becomes stronger with capital losses overhang. Thus, we put forth the following hypothesis:

**Hypothesis 2.** The short-term reversal effect is stronger in stocks with large aggregate capital losses.

### 3. Data and Methodology

In our study, we mainly use daily and monthly stock market data and accounting data. For stock market data, we get data from the Center for Research in Security Prices (CRSP). We include common stocks (share code 10 or 11) which are traded on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), or National Association of Securities Dealers Automated Quotations (NASDAQ). We filter out stocks that do not have price and trading volume data in past three years (756 trading days) to construct the variable CGO, and exclude stocks of which prices are less than \$5 or whose market cap is less than 5<sup>th</sup> percentile of NYSE breakpoint in the end of month of portfolio formation to remove unusual or microstructural effects driven from penny stocks. We mainly follow the method of constructing CGO as in Grinblatt and Han (2005) with slight modifications. For accounting data, we use COMPUSTAT and take variables that are used to construct the book value. We follow the methodology of Fama and French (1992) to construct book-to-market. In our main results, the returns of portfolios on July 1963 to December 2016, 642 monthly returns, are used.

For further analysis, we use institutional holdings data. First, we extract institutional ownership data from the Thomson Reuters Institutional Holdings (13F) database. In analyses using institutional holdings data, the data period is shrunk to the one from 1980:04 to 2016:12 because of data availability. Then, we follow the method of Abarbanell, Bushee, and Raedy (2003) to further classify institutional investors into two types, passive and active investors to compare with the work of Cheng et al. (2017).

For the CGO measure, we mainly follow the method of Grinblatt and Han (2005) but we use daily trading data instead of weekly data. An (2016) also use daily trading data while constructing his measure. We use daily data because we are doing our analysis in monthly frequency, which is different from Grinblatt and Han (2005) doing their analysis in weekly frequency. When we use weekly frequency to construct the CGO measure, our results hold, though not reported.

For each stock, we calculate the aggregate capital gains overhang (CGO) by the difference of the reference price, which is the aggregate purchase price, and the current price. Specifically, the reference price is defined as the turnover-weighted average of historical prices:

$$R_{i,t} = \sum_{n=0}^{\infty} (V_{i,t-n} \prod_{\tau=1}^n [1 - V_{i,t-n+\tau}]) P_{i,t-n} \quad (1)$$

In Equation (1),  $V_{i,t}$  stands for the stock  $i$ 's turnover at time  $t$  and  $P_{i,t}$  is stock  $i$ 's price at time  $t$ . We use past three year data and adjust our weights on prices to have the summation value 1. Then, the CGO measure is defined as the difference between the actual price and the reference price divided by the actual price, to proxy the unrealized capital gain or loss of investors in aggregate. Formally, our CGO measure is defined in Equation (2).

$$CGO_{i,t} = \frac{P_{i,t} - R_{i,t}}{P_{i,t}} \quad (2)$$

Many papers point out that it needs a caution to use the CGO measure constructed in Equation (2). Grinblatt and Han (2005) use weekly data to avoid the microstructural issues and give one week lag in their regression specifications. Actually, microstructural issues do not affect the core of our results. In specific, when we lag CGO measure or construct CGO measure in weekly frequency, the result is qualitatively unchanged. We reported our results for one-month lagged CGO measure and detailed discussions about the issues related to our CGO measures will be presented in Section 4.4.1

We first see the characteristics of the portfolios that are sorted by previous month return. In each month, stocks are sorted into ten deciles by previous month's holding period return (REV). In particular,



portfolio 1 (10) contains stocks of which prices went down (up) most in last one month.

[Table 1]

Table 1 reports the summary statistics of the decile portfolios sorted by REV as well as the long-short portfolio that buys portfolio 1, sells portfolio 10 and holds them for one month. All of the decile portfolios are equally-weighted. In each decile portfolio, we report future one month holding return (RET), its Carhart 4-factor alpha ( $\alpha$ ) (Carhart, 1997), cross-sectional ex-post skewness of one month return (PSK), formation month return (REV), market cap (MEQ), book-to-market ratio (BM), market beta (BETA), Amihud (2002)'s illiquidity measure (ILLIQ), turnover (TOVER), percentage of lottery stocks (LOTT) which are calculated using the method in Kumar (2009), stock price (LPRC), idiosyncratic volatility (IVOL), idiosyncratic skewness (ISKEW), and daily maximum return (MAX).

In Table 1, consistent with the finding of Jegadeesh (1990) and the previous literature, we can find economically and significantly meaningful future return difference between past one-month loser stocks (portfolio 1) and winner stocks (portfolio 10). Winner stocks underperform loser stocks by 0.82% per month ( $t=4.73$ ). Both winner and loser stocks have smaller size and larger previous 12-2 month cumulative returns. In addition, they exhibit low price, high idiosyncratic volatility, and high illiquidity, showing that those stocks are generally small and illiquid.

Because of the result of An et al. (2017), which documents reference-dependent preferences of lottery stocks, we also check the relationship between past month return and lottery characteristics. Winner stocks have high idiosyncratic skewness and high MAX, which are proxies for lottery variables. In general, two main lottery-proxy variables, LOTT and MAX, show consistent pattern that winner stocks tend to have more lottery-like features. We also see the ex-post one month return distribution to check whether there are more extreme returns in winner portfolios. In particular, we focus on cross-sectional skewness of ex-post one month returns in the portfolio. Empirically, we find that skewness of future returns is higher in group of winner stocks, and the difference between winner stocks and loser stocks is significant. In other words, the right tail of the distribution is heavier and there is more chance

to get extreme positive return in reversal winner portfolio. This empirical evidence indicates that there might exist some lottery-like behaviors of winner stocks.

[Table 2]

Table 2 reports the Pearson correlation table of our main variables. Among many correlation coefficients, we focus on correlations between CGO and other variables. Intuitively, the CGO measure proxies for the gain or loss of aggregate shareholders. Therefore, it is natural to think that our CGO measure can be correlated with historical returns. Because our main analysis is focusing on the dependence of the contrarian strategy in capital-gains-overhang states, it might be a big problem if there exists a large correlation between those variables. In fact, we find that there exists a meaningfully large correlation between CGO and REV (0.294). Even though it is not that large in scale to interrupt the double-sort or regression analysis, it may cause concerns and thus we mainly conduct dependent double-sort analysis, first by CGO and then by REV. The correlation between CGO and MOM is also quite large, 0.416, which is consistent with the existing literature and natural intuition. However, Grinblatt and Han (2005) show that CGO absorbs the predictability of MOM. Therefore, we may think that CGO has different and distinguishable effects to MOM. The correlations between LOGME, ILLIQ and REV are not that high. Those correlations are consistent with the pattern in Table 1, which is a U-shaped pattern. It means, stocks with extreme returns have small market cap and high illiquidity, while there is no significant directional pattern.

In addition, the correlations between IVOL, ISKEW, LPRC, MAX and REV show patterns consistent with those in Table 1. When REV is high, IVOL, ISKEW and MAX tend to have high value and LPRC shows the opposite, which all present lottery-like behavior. The correlation between CGO and lottery variables do not show consistent results, which may show that CGO is not much related to lottery feature.

## 4. Empirical Results

### 4.1. Reference-dependence of short-term reversal anomaly

Our main research question here is whether the liquidity provision depends on CGO especially for stocks experiencing buying pressure. Because investors are more willing to sell their stocks with large CGO, they are more willing to provide liquidity when the other investors want to buy. On the other hand, CGO is not related to the tendency to buy and thus it will not affect liquidity provision when the market wants to sell. Thus, liquidity provision increases with CGO in general, but especially for stocks with buying pressure. Thus, we expect that stocks with large CGO will have more liquidity than those with small CGO especially for stocks with buying pressure. That is, stocks with large CGO will have higher turnover and lower price impact than those with small CGO for stocks with buying pressure.

To test hypothesis 1 empirically, we employ two measures for liquidity that can capture the trading behavior of a stock in monthly frequency. Specifically, we use trading volume measure and price impact measure. If there are plentiful liquidity provider in certain stocks, then trading of stocks would be encouraged and price impact of each stocks will be reduced. Thus, we use two proxies to capture trading behavior.

First, we define abnormal turnover as the turnover of stocks scaled with previous 12-month turnover. Formally, we define abnormal turnover as following.

$$ABTOVER_{i,t} = \frac{TOVER_{i,t}}{TOVER_{i,t-12:t-1}} \quad (3)$$

We use abnormal turnover (ABTOVER) instead of raw turnover itself to reduce the influence from firm-specific historical trading behavior. Stocks with high ABTOVER are traded frequently compared to the historical trading magnitude of those stocks.

The second measure here we use to proxy trading behavior is a measure captures the price impact of trading in a stock. To proxy the price impact of an individual stock, we bring the well-known

illiquidity measure of Amihud (2002) (ILLIQ). Specifically, we calculate the ratio between the absolute return to dollar volume in a day and averaged it across each month for each stock. Therefore, we get average price impact proxy for each stock in each month. Intuitively, ILLIQ is the price variation of stock that a unit dollar of trading induces. Therefore, if there are plenty of liquidities provided, then the price impact would naturally decreases.

To confirm our hypothesis 1, we want to examine the effect of CGOs on the liquidity provision. In particular, we want to check the asymmetric influence of CGO in liquidity provision. Therefore, we conduct the following regression.

$$LQ_{i,t} = \alpha_0 + \alpha_1 CGO_{i,t} + (\beta_0 + \beta_1 CGO_{i,t}) REV_{i,t} + \gamma' Z_{i,t} + \varepsilon_{t+1} \quad (4)$$

In Equation (4),  $LQ_{i,t}$  stands for the liquidity variables used here, ABTOVER or ILLIQ.  $Z_{i,t}$  stands for the vector of various control variables including the log of market capitalization (LOGME), the log of book-to-market ratio (LOGBM), and daily return volatility in month t (VOL) of stocks, which are variables that is known to affect the liquidity of stocks. We also include the other liquidity variable as a control variable that are not used as dependent variable. Because our main purpose here is to see whether the relationship between the liquidity of stocks and buying pressure depends on the level of CGO, our focus is on the coefficient on the interaction term of CGO·REV,  $\beta_1$ . The estimation results for equation (3) are presented in Table 3.

[Table 3]

In Table 3, columns (1) and (2) are results employing ABTOVER as liquidity variables, while columns (3) and (4) are results using ILLIQ. Note that if liquidity is provided sufficiently, ABTOVER (ILLIQ) experiences high (low) level. In column (1) of Table 3, we can see the positive and significant ( $t=16.48$ ) coefficient on the interaction term between CGO and REV. It means that the positive effect of CGO to liquidity provision is pronounced among stocks with dominant buying pressure. Column (2) of Table 3 confirms our results in column (1) is not driven from other known characteristics that affect

liquidity. After controlling for other variables, the effect does not affected much ( $t=16.62$ ). Thus, column (1) and column (2) both support our hypothesis that selling pressure induced from CGO is an important factor for liquidity provision especially in stocks experiencing buying pressure. In column (3) of Table 3, we use ILLIQ instead of ABTOVER as an alternative variables. The result shows similar pattern. We can observe the negative and significant ( $t=-2.51$ ) coefficient on the interaction term between CGO and REV, which means that CGO affects price impact negatively in the group of stocks with recent rise. When we controls for other variables, negative relationship of the interaction term between CGO and REV and ILLIQ does not seems to be vanished but more pronounced ( $t=-4.90$ ). These evidences are consistent to the findings in columns (1) and (2), which employ ABTOVER as a liquidity measure.

Overall, results in Table 3 support hypothesis 1. Because behavioral biases lead liquidity providers to sell more stocks with large CGO, liquidity provision behavior is particularly active in stocks with buying pressure. As a consequence, stocks with buying pressure are especially sensitive to the magnitude of CGO, which is consistent to the empirical evidences presented in Table 3.

Thus far our interpretation of the results focuses on the argument that liquidity provision is closely linked to CGO. Our hypothesis here is whether there exists reference-dependence in the short-term reversal anomaly. In specific, we will focus on the question of whether there is any difference in the pattern of the short-term reversal depending on the capital-gain-overhanging states of shareholders. For the purpose of investigating the relation between capital gains overhang and the short-term reversal anomaly, we mainly conduct two types of analyses. First, we look at the returns after double-sorting stocks by previous one-month return and capital gains overhang. Next, we conduct the Fama-MacBeth (1973) regressions.

Table 4 shows the double-sort results. In this table, we use the dependent double-sort; in each month we first sort stocks in quintile by CGO, and then in each CGO-quintile we sort stocks in quintile by REV. In the table, REV 1 (REV 5) and CGO 1 (CGO 5) refer to the portfolio with lowest (highest)

previous one month return and lowest (highest) capital gains overhang, respectively. In addition to these 25 previous one month return and CGO double-sorted portfolios, we construct a zero-investment loser-minus-winner contrarian portfolio for each CGO-sorted quintile portfolio. We mainly report for the results in equal-weighted portfolios, but the result of value-weighted portfolios are somewhat weaker but represents qualitatively and quantitatively similar pattern as equal-weighted portfolios. Table 4 shows the dependent double-sort results.

[Table 4]

The results in Table 4 shows that short-term winners underperform short-term losers significantly in all quantiles. In the group of stocks with lowest CGO, the winner portfolio underperforms the loser portfolio by 1.41% per month ( $t=7.79$ ), while in the group of stocks with highest CGO quintile, the magnitude of underperformance drops to 0.4% per month ( $t=2.42$ ). The Contrarian strategy profit for the largest capital gain portfolio decreases by more than two-thirds compared to the largest capital loss portfolio. This difference-in-difference test confirms that the magnitude of the short-term reversal anomaly significantly ( $t=4.37$ ) varies among stocks with various CGO levels. When we control our returns using the Carhart four factors, the results are rarely affected. The risk-adjusted contrarian strategy profits are 0.32% per month for the largest CGO portfolio, which shows a marginal significance ( $t=1.92$ ), while those are 1.33% per month ( $t=6.67$ ) for the smallest CGO portfolio. The difference of contrarian strategy profits is similar to the case in unadjusted raw return, 1.01% per month, which indicates that our result stands firmly even after controlling for risk factors. In sum, the results in Table 4 shows that the short-term reversal effect becomes stronger for stocks with low CGO.

Next, we conduct the Fama-MacBeth regressions to further investigate the effect of CGOs on short-term reversal returns. Since the existing literature documents that stock returns are affected by various firm characteristics, the findings in Table 4 may be due to other variables related to CGOs. Unlike the double-sort analysis in Table 4, the Fama-MacBeth regression can control for the effects of other variables. Our Fama-MacBeth regressions have the following form:

$$Ret_{i,t+1} = \alpha_0 + \alpha_1 CGO_{i,t} + (\beta_0 + \beta_1 CGO_{i,t})REV_{i,t} + \gamma'Z_{i,t} + \varepsilon_{t+1} \quad (5)$$

In Equation (5),  $Z_{i,t}$  stands for the vector of various control variables. Our control variables include we include market beta (BETA), the log of market capitalization (LOGME), the log of book-to-market ratio (LOGBM), and the return over month t-11 to month t-1 (MOM) to capture the known risk factors, illiquidity (ILLIQ) proxied by Amihud's measure and share turnover (TURNOVER) to capture the trading pattern, idiosyncratic volatility in previous 6 months (IVOL), idiosyncratic skewness in previous 6 months (ISKEW), the log of the price per share in month t-1 (LPRC), and maximum daily return in month t (MAX) to adjust for the lottery characteristics described in Kumar (2009) and Bali et al. (2011). Because our main concern is to see whether the short-term reversal effect depends on the size of CGO, we will focus on the coefficient on the interaction term of CGO-REV,  $\beta_1$ . The estimation results for equation (5) are presented in Table 5.

[Table 5]

In column (1) of Table 5, we can see the positive contribution of CGO and negative contribution of REV to future returns, which are both consistent in previous studies. The negative coefficient of REV is the short-term reversal documented by Jegadeesh (1990). The positive coefficient of CGO shows the effect that investors are more likely to sell stocks with large CGO and thus the stock prices tend to go down from the selling pressure, which is documented by Grinblatt and Han (2005). In column (2), we run a regression with an interaction term between CGO and REV as well as REV and CGO. The coefficient on the interaction term is positive and statistically significant ( $t=6.90$ ). It means that the negative effect of REV is attenuated (strengthened) when CGO is high (low). In other words, the short-term reversal anomaly becomes more pronounced when CGO is low. Thus, column (2) of Table 5 confirms the result in Table 4. Column (3) of Table 5 examines whether our result can stand after other characteristics are controlled. After controlling for other characteristics, the effect of the interaction term not only survives, but also become stronger. The coefficient becomes larger (from 0.051 to 0.061), and more significant ( $t$ -value increases to 9.28). Interestingly, the effect of CGO becomes insignificant

and negative, which is contradictory to the finding by Grinblatt and Han. Thus, this table shows that CGO affects future returns mainly through the effect on the short-term reversal return after controlling for other characteristics. The coefficients of control variables are generally consistent with those in the literature.

The results documented in Tables 4 and 5 support our hypothesis: the short-term reversal effect is stronger in stocks with large aggregate capital losses. Because liquidity providers are more willing to sell their stocks with more CGO, they require less compensation for providing liquidity for those stocks. As the literature suggests, the short-term contrarian profits can be attributed to the compensation for the liquidity provision. (Nagel, 2012) Thus, the contrarian profits from the compensation for liquidity provisions should be greater for stocks with large CGO, which is confirmed in Tables 4 and 5.

## **4.2. Lottery-Based Explanation**

In the previous section, we document that the short-term reversal anomaly is more pronounced among small CGO stocks. We have argued that this strong tendency of short-term reversals among stocks with small CGO can be attributed to the larger compensation to liquidity provisions because investors or liquidity providers are less willing to sell stocks (or provide liquidity) when CGO is small. However, there may other explanations. For example, this might be due to investors' preference to lottery-like stocks. Bali et al. (2011) document that investors prefer and overvalue lottery-like stocks and thus there is underperformance among lottery-like stocks. Because overvalued lottery-like stocks are more likely to enjoy positive previous returns, this underperformance of lottery-like stocks may appear as short-term reversals. An et al. (2017) document that the underperformance of lottery-like stocks is reference-dependent and it appears mostly among stocks with small CGO while it becomes insignificant among stocks with large CGO. Considering that hat recent winner stocks have ex-ante lottery-like feature and ex-post positively skewed return distribution in Tables 1 and 2, it is possible that



our results are driven by the lottery-like features of our winners. Thus, in this section we will check whether our results can be accounted for by the lottery-like feature of our winner portfolio.

We conduct the following Fama-MacBeth regressions:

$$R_{i,t+1} = \alpha_0 + \alpha_1 CGO_{i,t} + (\beta_0 + \beta_1 CGO_{i,t}) REV_{i,t} + (\gamma_0 + \gamma_1 CGO_{i,t}) X_{i,t} + \gamma' Z_{i,t} + \varepsilon_{t+1} \quad (6)$$

Here,  $X_{i,t}$  stands for a proxy for lottery-like feature and all other variable definitions are the same as in equation (5).  $X_{i,t}$  and an interaction term between  $X_{i,t}$  and CGO are included to control for the reference-dependent effect of lottery preference. In this paper, we will show the results when we use MAX used in Bali et al., but our results are qualitatively the same when we use the jackpot probability of Conrad, Kapadia, and Xing (2014). If our results are totally driven from the lottery feature or max effect, then the coefficient of CGO·REV  $\beta_1$  will be indistinguishable to zero. Table 6 shows the estimated Fama-MacBeth regression results.

[Table 6]

In Table 6, columns (1) and (3) are regression results without controlling for the lottery proxy from Table 5, which are presented for comparisons for the cases with the lottery proxy in Equation (6). First, in column (2), we can see that the explanation power of the interaction term between REV and CGO is still very significant ( $t=5.54$ ). Compared to the result in column (1), the significance of the interaction term between REV and CGO decreases slightly but survives firmly even after controlling for the max effect documented in Ahn et al. The coefficient of the interaction term between MAX and CGO in column (2) is also positive and significant ( $t=8.68$ ). Since MAX is known as a negative predictor of the expected return, the significant and positive coefficient of that interaction term means that the negative predictability of MAX becomes strengthened when CGO is low, which is consistent with the findings by An et al. (2017) and Hur and Singh (2017). In column (4), we control for various characteristics used in equation (5) reported in Table 5 as well as the max effect. The result of column (4) shows that the

coefficient of the interaction term, CGO·REV is still positive and significant ( $t=6.09$ ) after controlling for various characteristics and the max effect. The interaction term between MAX and CGO is also significant and positive ( $t=7.51$ ) in this specification. Thus, the max effect seems to be an important determinant for future stock returns, but does not account for the relation between the short-term reversal and CGO. The relation between the short-term reversal and CGO we are documenting is a distinct phenomenon that cannot be fully explained by the existing lottery-related findings

### 4.3. Relation to the study of Cheng et al. (2017)

Cheng et al. (2017) find that the magnitude of short-term reversal anomaly is larger for loser stocks in the previous quarter. Because they look at the short-term reversal return conditional on t-4 to t-2 month returns (QMOM), their conditional variable QMOM is closely related to our measure CGO in the sense that both of them use past stock return performance. In fact, the correlation between CGO and QMOM or MOM is 0.367 and 0.416, respectively. In this section, we examine whether our result is just another representation of their empirical finding.

We look at the following Fama-MacBeth regressions:

$$\begin{aligned}
 R\epsilon_{i,t+1} = & \alpha_0 + \alpha_1 CGO_{i,t} + \alpha_2 QMOM_{i,t} + (\beta_0 + \beta_1 CGO_{i,t} + \beta_2 QMOM_{i,t}) REV_{i,t} \\
 & + \gamma' Z_{i,t} + \epsilon_{t+1}
 \end{aligned} \tag{7}$$

In Equation (7),  $QMOM_{i,t}$  represents the return of stock i from t-4 month to t-2 month, which is the variable constructed in the same manner to Cheng et al. (2017). Even though their main analysis is conducted based on QMOM, we also examine the case when MOM is used in equation (7) in place of QMOM for robustness. Our main focus in this regression is the coefficient of CGO,  $\beta_1$ . If our result is mainly driven by the empirical finding of Cheng et al. (2017), then the effect of CGO will be subsumed by QMOM and the coefficient  $\beta_1$  will not be significantly different from zero. Table 7 shows the result.

[Table 7]

In Table 7, columns (1) and (2) confirm the findings of Cheng et al. (2017). The coefficient of REV·QMOM is positive and statistically significant ( $t=5.35$ ). Even when we use MOM in place of QMOM, the coefficient of REV·MOM is still positive and significant, though  $t$ -statistics become a little smaller ( $t=4.66$ ). When we add CGO and an interaction term of REV and CGO in our regressions shown in columns (3) and (4) of the table, the magnitude of the coefficients is reduced to almost half (0.071 to 0.042 for QMOM and 0.028 to 0.01 for MOM) and their significance levels are also significantly reduced. More importantly, the coefficient of REV·CGO is positive and statistically significant ( $t=9.93$  and  $t=9.09$ , respectively) in both cases. The economic magnitude also does not change much compared to the result in Table 5. (0.057 or 0.054 vs. 0.061 in Table 5)

In sum, our results stand on its own when compared to Cheng et al. (2017). The short-term reversal effect is stronger in stocks with large aggregate capital losses, and it is so even after controlling for past one-quarter or two-quarter performance.

Cheng et al. (2017) also claim that active institutions are more likely to provide liquidity. In their paper, the exit of active institutional investors lead the enhancement of the short-term reversal strategy profit. We examine whether our results hold after the institutional investor exit effect is controlled. In specific, we use a dummy variable that gets 1 if active institutional investors exit in the past quarter as a control variable (EXIT\_D). Our estimation and test strategy is similar to the case in equation (7) except that we use EXIT\_D in place of QMOM. Table 8 shows the result.

[Table 8]

Due to the availability of institutional holding data, the sample period in this table is reduced to 1980:08-2016:12. Column (1) shows that the reference-dependency of the short-term reversal still holds for this sample period. The coefficient of REV·CGO is 0.050, which is similar to the one for the whole sample period, and statistically significant ( $t=7.09$ ). Column (2) of the table confirms Chen et al.

(2017)'s finding. When institutional investors exit, the short-term reversal becomes stronger: the coefficient of  $REV \cdot EXIT\_D$  is negative and statistically significant ( $t=-3.91$ ). In column (3), when we include both interaction terms, the coefficient of the interaction term between  $REV$  and  $CGO$  does not change much either statistically ( $t=7.05$ ) or in magnitude (0.049). In contrast, the dependency of the short-term reversal on institutional exits significantly decreases in magnitude (-0.013 to -0.007) or in significance ( $t=-3.91$  to -2.15). This evidence shows that our result stands firmly even after controlling for the institutional exit effect.

#### **4.4. Robustness Check**

In this section, we conduct robustness checks for our results. First, we examine whether a measure of selling pressure different from  $CGO$  changes our results. Because  $CGO$  is used in our paper to measure selling pressure, different selling pressure measures may lead to the same conclusion as ours, if the measures properly proxy for selling pressure. Second, we check whether different definitions of  $CGO$  change our results. Third, we check whether  $CGO$  for stocks with a large portion of institutional holdings has a different meaning than  $CGO$  for those with a small portion of institutional holdings. Fourth, we will examine whether our results change when applied to industry-adjusted short-term reversal returns.

##### **4.4.1. Different CGOs**

In our main analysis, we have constructed the  $CGO$  measure using daily closing prices. Those raw prices are the prices that are not adjusted for stock splits, dividends, or other possible effects that can affect stock prices. Therefore, an incline or decline of a raw stock price does not necessarily mean a gain or loss. The  $CGO$  measure is constructed in that manner because naïve investors tend to focus on the price that they bought and care less about the events that affect the stock price. For the purpose of robustness, we do the same analyses reported in the paper with the new  $CGO$  using the adjusted prices

of stocks instead of the raw prices. The results are qualitatively the same: The short-term reversal effect is stronger for stocks with small CGO with or without controlling for other characteristics.

We also conduct all the analyses using one-month lagged CGOs instead of CGOs. Our main argument is driven by selling pressure for the previous one-month period. While CGO captures the selling pressure at the end of this one-month period, the lagged CGO captures the selling pressure at the beginning of this one-month period. Thus, the lagged CGO is another good proxy for selling pressure. Even with the lagged CGO, all the results remain qualitatively the same.

[Table 9]

#### 4.4.2. Institutional Investors' Holdings and the CGO Effect

Our motivation for this paper comes from one of the behavioral biases, disposition effect. This behavioral bias is believed to be stronger among individual investors than institutional investors. Thus, it is reasonable to assume that our results become stronger for stocks with low institutional investors'.

Following Nagel (2005), we calculate the residual institutional ownership (RI) by removing the size effect. Then we divide our sample stocks into two groups: one with above-median RI and the other with below-median RI. Then we conduct the double-sort analysis in Table 4 for the two RI groups. Table 10 shows the result.

[Table 10]

Panel A of Table 10 shows the result for the above-median RI group, while Panel B of the table shows the result for the below-median RI group. First, we can see that short-term reversals are prevalent for all cases with or without risk adjustment except for the largest CGO portfolio in the below-median RI group. Second, the short-term reversal effect is stronger for stocks with small CGO in both groups. The short-term reversal profit decreases monotonically with CGO in both groups. Thirst, most importantly, the extent of the CGO effect on the short-term reversal return is higher for the below-

median RI group than for the above-median RI group. The difference-in-difference test shows that the difference of the return on the long-short contrarian portfolio between the largest and smallest CGO cases is 0.65% and 0.54% per month with and without risk adjustment for the above-median RI group, respectively, while it is 1.22% and 1.31% per month for the below-median RI group respectively. The statistical significances are also larger for the below-median RI group than for the above-median RI group ( $t=3.80$  and  $3.81$  vs.  $1.85$  and  $2.19$ ). Thus, we can confirm that the CGO effect is stronger for stocks with low institutional investors' holdings or high individual investors' holdings, though the CGO effect documented in this paper is prevalent, regardless of institutional institutions' holdings.

#### 4.4.3. Industry-adjusted short-term reversal effect

Hameed and Mian (2015) hypothesize that if short-term reversal comes from deviations from fundamental values due to liquidity shocks and subsequent convergence, industry-adjusted returns show clearer return reversals because returns on firms in the same industry are closely related and more likely to be affected by the same fundamentals, and provide evidence for industry-adjusted short-term reversals. Hameed and Mian show that short-term contrarian phenomenon is pronounced when the return is adjusted using industry return. They argue that the stronger reversal is shown because of that residual is likely generated from liquidity trade, compared to fundamental issue. Asparouhova, Bessembinder, and Kalcheva (2013) and Da, Liu, and Schaumburg (2014) also confirm Hameed and Mian. In this section, we examine the relation between industry-adjusted returns and CGO. Because CGO represents selling pressure and the supply of liquidity in our framework, the results should remain the same, considering that industry-adjusted returns are more related to liquidity shocks. Using the 49 industry specifications by Fama and French (1997), we calculate the industry-adjusted return of a stock as the difference between the return of the stock and the industry portfolio return to which the stock belongs to. We conduct the same double-sort analysis as in Table 4 except that we use industry-adjusted returns instead of raw returns. The results are given in Table 11:

[Table 11]

Table 11 shows that the short-term reversal becomes strengthened in general, which is consistent with Hameed and Mian (2015). More importantly, the difference-in-difference test shows that short-term reversals for stocks with small CGO are larger than those for stocks with large CGO. It confirms once again our hypothesis.

## 6. Conclusion

The short-term reversal is widely known in the literature and often interpreted as the compensation for providing liquidity. In this paper, we document that the short-term return reversal is more pronounced for stocks with small CGO. As Kaniel et al. (2008) document, individual investors are liquidity providers and tend to sell stocks with large CGO, while they do not have any preference when they buy stocks. Thus, stocks with large CGO will require less compensation for liquidity provision when investors want to buy those stocks, while there are no liquidity difference between stocks with large CGO and those with small CGO when investors want sell the stocks. This implies that short-term reversal should be more pronounced for stocks with low CGO.

Our paper provides the following empirical findings:

- (1) Stocks with large CGO have more turnovers and less price impacts than those with small CGO. That is, more liquidity seems to be provided for stocks with large CGO.
- (2) The average return on the long-short contrarian portfolio buying short-term losers and selling short-term winners is positive in general. More importantly, it becomes larger and more significant for stocks with small CGO. That is, the short-term reversal is more pronounced for stocks with small CGO.
- (3) The negative relation between the return on the long-short contrarian portfolio and CGO stands firmly even after controlling for risk, lottery preference, previous returns and other

characteristics known in the literature.

- (4) The negative relation between the return on the long-short contrarian portfolio and CGO becomes stronger for stocks with less institutional holdings.

Our paper is based on the prospect theory developed by Kahneman and Tversky (1979). Our contribution is to apply the prospect theory to the short-term reversal anomaly and provide empirical evidence supporting its implication.



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**Table 1. Summary statistics of REV portfolios.**

Table 1 represents summary statistics for portfolios sorted by the previous month return (REV). Decile 1 portfolio contains stocks that their previous month return is in lowest decile, while Decile 10 portfolio is constructed opposite. 1-10 is a zero-investment return which longs Decile 10 portfolio and shorts Decile 1 portfolio. Summary statistics include monthly raw return (RET), Carhart 4-factor adjusted return ( $\alpha$ ), cross-sectional ex-post skewness of one month return (PSK), previous month return (REV), market beta (BETA), market cap, scale of  $10^6$ \$ (MEQ), book-to-market ratio (BM), previous 12-2 month cumulative holding return (MOM), illiquidity measure (ILLIQ), monthly turnover (TOVER), proportion of lottery stocks (LOTT), lag price of stock (LPRC), idiosyncratic volatility (IVOL), idiosyncratic skewness (ISKEW), and maximum daily return (MAX). Sample period is from 1963:07 to 2016:12.

REV decile	RET	$\alpha$	PSK	REV	BETA	MEQ	BM	MOM	ILLIQ	TOVER	LOTT	LPRC	IVOL	ISKEW	MAX
1 (Low)	1.50	0.38	0.54	-14.53	1.37	1414.54	0.75	26.52	10.19	0.10	27%	27.50	2.65	0.09	2.74
2	1.53	0.41	0.57	-7.23	1.19	2412.25	0.79	20.01	9.60	0.07	21%	44.84	2.16	0.28	2.43
3	1.38	0.28	0.61	-4.20	1.11	2871.97	0.80	18.57	9.44	0.06	18%	56.92	1.99	0.32	2.36
4	1.26	0.16	0.53	-1.97	1.06	3229.76	0.81	17.65	8.85	0.06	16%	58.10	1.90	0.34	2.36
5	1.24	0.15	0.61	-0.02	1.05	3278.07	0.81	17.40	8.32	0.06	15%	69.72	1.87	0.35	2.43
6	1.13	0.05	0.54	1.90	1.05	3289.10	0.81	17.60	8.24	0.06	15%	53.93	1.87	0.36	2.56
7	0.99	-0.09	0.61	4.01	1.07	3231.30	0.81	18.09	8.12	0.06	16%	60.38	1.91	0.37	2.75
8	0.99	-0.09	0.65	6.59	1.12	3101.40	0.80	18.54	8.15	0.07	18%	49.40	2.00	0.39	3.07
9	0.80	-0.33	0.62	10.42	1.19	2619.65	0.80	20.61	8.58	0.08	24%	37.76	2.18	0.45	3.62
10 (High)	0.68	-0.48	0.78	22.38	1.34	1417.00	0.84	26.81	10.04	0.11	41%	27.92	2.80	0.78	5.43
1 - 10	0.82 (4.73)	0.87 (4.44)	-0.24 (-3.95)												

**Table 2. Correlations.**

Table 2 represents the time-series average of cross-sectional correlations between characteristics of stocks. In each month, cross-sectional correlation between characteristics is calculated and that correlation is averaged across sample period. Sample period is from 1963:07 to 2016:12.

	REV	CGO	BETA	LOGME	LOGBM	MOM	ILLIQ	TOVER	IVOL	ISKEW	LPRC	MAX
REV	1	0.294	0.010	-0.005	0.027	0.012	0.004	0.129	0.098	0.175	-0.083	0.500
CGO		1	-0.082	0.069	0.075	0.416	-0.018	0.027	-0.141	0.157	0.237	-0.023
BETA			1	-0.091	-0.128	0.065	-0.061	0.281	0.404	0.039	-0.153	0.355
LOGME				1	-0.202	-0.002	-0.357	0.040	-0.465	-0.118	0.642	-0.292
LOGBM					1	0.018	0.108	-0.067	-0.090	0.073	-0.186	-0.069
MOM						1	-0.021	0.155	0.124	0.156	0.167	0.051
ILLIQ							1	-0.126	0.139	0.049	-0.183	0.100
TOVER								1	0.345	0.052	0.005	0.395
IVOL									1	0.226	-0.512	0.679
ISKEW										1	-0.079	0.173
LPRC											1	-0.390
MAX												1

**Table 3. Variation of the liquidity to capital gains overhang (CGO).**

Table 3 represents the results from Fama-Macbeth (1973) regression. The dependent variables are abnormal turnover of stock in columns (1) and (2), price impact of stock in columns (3) and (4), and independent variables are previous month return (REV), capital gains overhang (CGO), the interaction term between REV and CGO, and various control variables. T-statistics are calculated following the method of Newey-West (1987) and represented in parentheses. Sample period is from 1963:07 to 2016:12.

	(1)	(2)	(3)	(4)
INTERCEPT	0.086 (112.64)	0.024 (7.11)	7.931 (6.54)	91.402 (5.79)
REV	0.002 (12.51)	0.001 (11.37)	-0.001 (-0.13)	0.029 (2.59)
CGO	0.009 (6.84)	0.018 (10.48)	-3.456 (-3.55)	-0.470 (-1.12)
REV X CGO	0.004 (16.48)	0.003 (16.62)	-0.050 (-2.51)	-0.122 (-4.90)
LOGME		0.002 (9.39)		-6.678 (-5.64)
LOGBM		0.006 (10.99)		0.487 (2.46)
VOL		0.018 (29.34)		0.311 (1.03)
ABTOVER				-27.423 (-6.40)
ILLIQ		-0.001 (-4.07)		

**Table 4. Variation of the short-term reversal strategy profits to capital gains overhang (CGO).**

Table 4 represents the result of the dependent double sort analysis. In each month, we divide all stocks into five quintiles using capital gains overhang (CGO). In each quintile, we further sort stocks using previous month return (REV). We report one-month equal-weighted holding period return of each portfolio. T-statistics are calculated following the method of Newey-West (1987) and represented in parentheses. Sample period is from 1963:07 to 2016:12.

		REV						
		1(Low)	2	3	4	5(High)	1-5	1-5 (4 Factor)
CGO	1(Low)	1.55	1.51	1.28	0.93	0.15	1.41 (7.79)	1.33 (6.67)
	2	1.39	1.34	1.15	0.96	0.22	1.17 (7.88)	1.00 (6.21)
	3	1.46	1.33	1.13	0.93	0.47	0.99 (7.33)	0.87 (5.63)
	4	1.56	1.23	1.12	0.96	0.77	0.79 (6.23)	0.62 (4.39)
	5(High)	1.84	1.51	1.33	1.26	1.44	0.40 (2.42)	0.32 (1.92)
	1-5						1.00 (4.37)	1.02 (4.42)

**Table 5. Fama-Macbeth regressions.**

Table 5 represents the results from Fama-Macbeth (1973) regression. The dependent variable is monthly raw return of stock, and independent variables are previous month return (REV), capital gains overhang (CGO), the interaction term between REV and CGO, and various control variables. T-statistics are calculated following the method of Newey-West (1987) and represented in parentheses. Sample period is from 1963:07 to 2016:12.

	(1)	(2)	(3)
INTERCEPT	1.164 (5.76)	1.140 (5.75)	3.909 (7.27)
REV	-0.030 (-7.56)	-0.027 (-7.11)	-0.024 (-5.37)
CGO	0.608 (4.11)	0.579 (3.60)	-0.145 (-1.30)
REV X CGO		0.051 (6.90)	0.061 (9.28)
BETA			16.206 (1.94)
LOGME			-0.127 (-4.15)
LOGBM			0.121 (2.14)
MOM			0.008 (6.02)
ILLIQ			-0.011 (-1.64)
TURNOVER			0.977 (1.95)
IVOL			-0.366 (-5.70)
ISKEW			0.072 (4.10)
LPRC			-0.170 (-2.75)
MAX			-0.101 (-4.33)



**Table 6. Lottery characteristics and the short-term reversal strategy.**

Table 6 represents the results from Fama-Macbeth (1973) regression. The dependent variable is monthly raw return of stock, and independent variables are previous month return (REV), maximum daily return (MAX), capital gains overhang (CGO), interaction term between REV and CGO, interaction term between MAX and CGO, and various control variables. T-statistics are calculated following the method of Newey-West (1987) and represented in parentheses. Sample period is from 1963:07 to 2016:12.

	(1)	(2)	(3)	(4)
INTERCEPT	1.140 (5.75)	3.909 (7.27)	3.909 (7.27)	3.785 (6.91)
REV	-0.027 (-7.11)	-0.022 (-3.35)	-0.024 (-5.37)	-0.027 (-6.01)
MAX		-0.101 (-4.33)	-0.101 (-4.33)	-0.070 (-3.17)
CGO	0.579 (3.60)	-0.633 (-3.35)	-0.145 (-1.3)	-1.144 (-6.97)
REV X CGO	0.051 (6.90)	0.038 (5.54)	0.061 (9.28)	0.042 (6.09)
MAX X CGO		0.353 (8.68)		0.311 (7.51)
BETA			16.206 (1.94)	16.044 (1.92)
LOGME			-0.127 (-4.15)	-0.130 (-4.16)
LOGBM			0.121 (2.14)	0.122 (2.15)
MOM			0.008 (6.02)	0.008 (5.95)
ILLIQ			-0.011 (-1.64)	-0.012 (-1.82)
TURNOVER			0.977 (1.95)	0.840 (1.72)
IVOL			-0.366 (-5.70)	-0.366 (-5.64)
ISKEW			0.072 (4.10)	0.072 (4.23)

LPRC

-0.170  
(-2.75)

-0.140  
(-2.24)

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**Table 7. Past performances and the short-term reversal strategy.**

Table 7 represents the results from Fama-Macbeth (1973) regression. The dependent variable is monthly raw return of stock, and independent variables are previous month return (REV), capital gains overhang (CGO), past 12-2 month cumulative holding return (MOM), past 4-2 month cumulative holding return (QMOM), interaction term between REV and CGO, interaction term between REV and MOM, interaction term between REV and QMOM, and various control variables. T-statistics are calculated following the method of Newey-West (1987) and represented in parentheses. Sample period is from 1963:07 to 2016:12.

	(1)	(2)	(3)	(4)
INTERCEPT	3.898 (7.20)	3.874 (7.25)	3.902 (7.28)	3.916 (7.38)
REV	-0.034 (-6.56)	-0.028 (-5.55)	-0.027 (-5.68)	-0.022 (-4.85)
CGO			-0.140 (-1.26)	-0.201 (-2.01)
MOM	0.007 (5.07)		0.008 (6.00)	
QMOM		0.008 (3.77)		0.010 (4.56)
REV X CGO			0.057 (9.93)	0.054 (9.09)
REV X MOM	0.028 (4.66)		0.010 (2.11)	
REV X QMOM		0.071 (5.35)		0.042 (3.45)
BETA	15.050 (1.84)	13.277 (1.63)	16.068 (1.94)	14.171 (1.72)
LOGME	-0.126 (-4.06)	-0.124 (-4.09)	-0.125 (-4.11)	-0.128 (-4.25)
LOGBM	0.117 (2.07)	0.116 (2.09)	0.121 (2.13)	0.121 (2.17)
IMOM		0.008 (5.08)		0.009 (5.83)
ILLIQ	-0.011 (-1.63)	-0.011 (-1.65)	-0.011 (-1.64)	-0.011 (-1.66)
TURNOVER	1.364	1.298	1.043	1.054

	(2.67)	(2.55)	(2.07)	(2.06)
IVOL	-0.328	-0.340	-0.361	-0.380
	(-5.23)	(-5.48)	(-5.66)	(-5.92)
ISKEW	0.067	0.060	0.072	0.064
	(3.97)	(3.53)	(4.17)	(3.74)
LPRC	-0.187	-0.191	-0.173	-0.172
	(-2.94)	(-3.15)	(-2.81)	(-2.86)
MAX	-0.087	-0.086	-0.103	-0.011
	(-3.84)	(-3.86)	(-4.49)	(-1.66)

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**Table 8. Active institutional investors and the short-term reversal strategy.**

Table 8 represents the results from Fama-Macbeth (1973) regression. The dependent variable is monthly raw return of stock, and independent variables are previous month return (REV), capital gains overhang (CGO), the dummy variable that has value 1 when active institutions exist (EXIT\_D), interaction term between REV and CGO, interaction term between REV and EXIT\_D, and various control variables. T-statistics are calculated following the method of Newey-West (1987) and represented in parentheses. Sample period is from 1980:08 to 2016:04.

	(1)	(2)	(3)
INTERCEPT	3.515 (5.57)	3.586 (5.72)	3.550 (5.66)
REV	-0.013 (-2.81)	-0.010 (-2.00)	-0.010 (-1.98)
CGO	-0.151 (-1.20)	-0.244 (-2.17)	-0.162 (-1.31)
EXIT_D		-0.083 (-2.27)	-0.081 (-2.18)
REV X CGO	0.050 (7.09)		0.049 (7.05)
REV X EXIT_D		-0.013 (-3.91)	-0.007 (-2.15)
BETA	4.317 (0.44)	3.591 (0.37)	4.379 (0.45)
LOGME	-0.106 (-3.01)	-0.117 (-3.28)	-0.108 (-3.03)
LOGBM	0.091 (1.43)	0.092 (1.46)	0.091 (1.44)
QMOM	0.007 (2.61)	0.007 (2.75)	0.007 (2.47)
IMOM	0.007 (4.09)	0.007 (4.12)	0.007 (3.98)
ILLIQ	-0.018 (-1.82)	-0.019 (-1.92)	-0.019 (-1.93)
TURNOVER	0.453 (0.97)	0.936 (1.87)	0.471 (1.00)
IVOL	-0.280	-0.270	-0.275

	(-4.04)	(-3.87)	(-3.94)
ISKEW	0.035	0.030	0.033
	(1.81)	(1.55)	(1.73)
LPRC	-0.107	-0.091	-0.106
	(-1.66)	(-1.41)	(-1.64)
MAX	-0.116	-0.106	-0.117
	(-4.38)	(-4.10)	(-4.43)

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**Table 9. Robustness check: alternatively defined CGO.**

Table 9 represents the results from Fama-Macbeth (1973) regression. The dependent variable is monthly raw return of stock, and independent variables are previous month return (REV), alternatively defined CGO (capital gains overhang using adjusted price (CGOa) in columns (1) and (2), lagged CGO (lagCGO) in columns (3) and (4)), interaction term between REV and CGOa, and various control variables. T-statistics are calculated following the method of Newey-West (1987) and represented in parentheses. Sample period is from 1963:07 to 2016:12.

	(1)	(2)	(1)	(2)
INTERCEPT	3.888 (7.23)	3.772 (6.86)	3.816 (7.12)	3.761 (6.96)
REV	-0.035 (-6.83)	-0.036 (-7.11)	-0.024 (-5.04)	-0.025 (-5.29)
CGO	0.449 (2.44)	-0.953 (-3.56)	-0.127 (-1.20)	-0.447 (-3.04)
REV X CGO	0.072 (7.48)	0.043 (4.48)	0.044 (6.30)	0.037 (4.75)
MAX X CGO		0.420 (7.47)		0.093 (2.42)
BETA	15.452 (1.89)	15.136 (1.85)	14.755 (1.78)	14.436 (1.74)
LOGME	-0.116 (-3.83)	-0.116 (-3.79)	-0.126 (-4.13)	-0.127 (-4.13)
LOGBM	0.131 (2.33)	0.122 (2.19)	0.119 (2.11)	0.119 (2.11)
MOM	0.006 (4.63)	0.006 (4.77)	0.008 (5.91)	0.008 (5.88)
ILLIQ	-0.011 (-1.49)	-0.011 (-1.50)	-0.011 (-1.61)	-0.011 (-1.65)
TURNOVER	1.253 (2.50)	1.078 (2.19)	1.377 (2.71)	1.322 (2.62)
IVOL	-0.333 (-5.27)	-0.329 (-5.20)	-0.336 (-5.29)	-0.340 (-5.34)
ISKEW	0.064 (3.66)	0.066 (3.88)	0.066 (3.75)	0.068 (3.96)
LPRC	-0.222	-0.186	-0.168	-0.155

	(-3.80)	(-3.16)	(-2.70)	(-2.46)
MAX	-0.098	-0.090	-0.085	-0.065
	(-4.18)	(-4.08)	(-3.76)	(-2.92)

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**Table 10. Robustness check: subsamples classified by the residual institutional ownership.**

Table 10 represents the results of the dependent double sort analysis. In each month, we divide all stocks into five quintiles using capital gains overhang (CGO). In each quintile, we further sort stocks using previous month return (REV). We report one month equal-weighted holding return of each portfolio. Panel A represents the result using stocks which have residual institutional ownership (RI) above average, while Panel B represents using stocks which have RI below average. T-statistics are calculated following the method of Newey-West (1987) and represented in parentheses. Sample period is from 1980:08 to 2016:12.

Panel A. RI above Median		REV						
		1(Low)	2	3	4	5(High)	1-5	1-5 (4 Factor)
CGO	1(Low)	1.72	1.60	1.50	1.19	0.56	1.16 (5.24)	1.10 (4.45)
	2	1.42	1.40	1.38	1.15	0.35	1.06 (5.43)	0.89 (4.65)
	3	1.52	1.32	1.17	0.91	0.60	0.92 (5.34)	0.76 (3.93)
	4	1.68	1.45	1.22	0.97	0.84	0.85 (4.65)	0.65 (3.26)
	5(High)	2.07	1.51	1.42	1.25	1.44	0.62 (3.03)	0.45 (2.03)
	1-5						0.54 (1.85)	0.65 (2.19)
Panel B. RI below Median		REV						
		1(Low)	2	3	4	5(High)	1-5	1-5 (4 Factor)

CGO	1(Low)	1.09	1.36	1.22	1.03	-0.05	1.15 (4.46)	0.95 (3.47)
	2	1.20	1.28	1.25	1.04	0.39	0.81 (4.66)	0.50 (2.77)
	3	1.27	1.35	1.18	1.07	0.54	0.73 (4.54)	0.56 (2.89)
	4	1.45	1.31	1.27	1.15	0.77	0.68 (3.34)	0.51 (2.52)
	5(High)	1.61	1.56	1.38	1.39	1.77	-0.16 (-0.64)	-0.27 (-1.25)
	1-5						1.31 (3.81)	1.22 (3.80)

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**Table 11. Robustness check: industry-adjusted short-term reversal strategy.**

Table 11 represents the result of the dependent double sort analysis. In each month, we divide all stocks into five quintiles using capital gains overhang (CGO). In each quintile, we further sort stocks using the residual part of previous month return in net of the portfolio return that stock is belonging (REV\_IND). REV\_IND is calculated as the difference between previous month return of stock (REV) and the return of industry portfolio that stock is belonging. We report one month equal-weighted holding return of each portfolio. T-statistics are calculated following the method of Newey-West (1987) and represented in parentheses. Sample period is from 1963:07 to 2016:12.

		REV_IND						
		1(Low)	2	3	4	5(High)	1-5	1-5 (4 Factor)
CGO	1(Low)	1.77	1.50	1.19	0.97	-0.01	1.78 (9.36)	1.67 (8.18)
	2	1.60	1.41	1.20	0.80	0.07	1.54 (10.16)	1.37 (8.48)
	3	1.75	1.35	1.08	0.86	0.29	1.46 (10.46)	1.31 (8.26)
	4	1.69	1.44	1.06	0.84	0.60	1.10 (9.28)	0.92 (7.45)
	5(High)	2.03	1.54	1.26	1.21	1.33	0.71 (4.52)	0.62 (4.15)
	1-5						1.08 (5.09)	1.05 (4.96)