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# Lottery-Related Anomalies: The Role of Reference-Dependent Preferences

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**Abstract.** Previous empirical studies find that lottery-like stocks significantly underperform their non-lottery-like counterparts. Using five different measures of the lottery features in the literature, we document that the anomalies associated with these measures are state dependent: the evidence supporting these anomalies is strong and robust among stocks where investors have lost money, whereas among stocks where investors have gained profits, the evidence is either weak or even reversed. Several potential explanations for such empirical findings are examined, and we document support for the explanation based on reference-dependent preferences. Our results provide a unified framework to understand the lottery-related anomalies in the literature.

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## 1. Introduction

Numerous studies have found that lottery-like stocks tend to significantly underperform nonlottery-like stocks using various measures of lottery features. A popular explanation is that investors have a strong preference for lottery-like assets, leading to the overpricing of these assets. In the data, lottery-like assets usually have a small chance of earning extremely high returns. The overweighting of the probability of these extremely high returns could, in theory, induce a strong preference for lottery-like assets (e.g., Barberis and Huang 2008). Indeed, the overweighting of small probability events is a key feature of prospect theory (PT) utility. The explanation based on the probability weighting implies an *unconditional* preference for lottery-like assets: investors prefer lottery-like assets regardless of their prior performance.[1] However, we document in this paper that the evidence for the lottery-related anomalies depends on whether investors are in a gain or loss region relative to a reference point.

daily returns in the previous month). In sharp contrast, among firms with large prior capital gains (top quintile of CGO), the returns of lottery-like stocks measured by maximum daily returns are 54 bps higher per month than those of nonlottery-like stocks. Similar results hold when the lottery feature is measured by predicted jackpot probability, expected idiosyncratic skewness, failure probability, and bankruptcy probability. In addition, our results still hold when we control for a battery of additional variables, such as firm size, the book-to-market ratio, share turnover, and return volatility in the regressions of Fama and MacBeth (1973).

These findings suggest that the lottery-related anomalies depend on whether investors are in the gain or loss territory relative to a reference point. Moreover, our results are robust across all of the five lottery measures, although these measures were initially motivated by different concepts. Our empirical findings suggest that a common underlying force may have played a crucial role in all of these anomalies, and understanding these anomalies calls for a unified framework. Therefore, we go on to examine several possible explanations for our empirical findings. For the first explanation, we investigate the roles of reference-dependent preferences (RDPs) and mental accounting (MA) in these lottery-related anomalies. The key idea underlying MA is that decision makers tend to mentally frame different assets as belonging to separate accounts and then apply RDP to each account by ignoring possible interaction among these assets. The MA of Thaler (1980, 1985) provides a theoretical foundation for studies in which decision makers set a reference point for each asset they own.

With RDP, investors' risk-taking behavior in the loss region can be different from that in the gain region. For example, PT posits that individuals tend to be risk seeking in the loss region. In addition, individuals could also have a strong desire to break even after prior losses relative to a reference point (the break-even effect). Lottery-like assets are particularly attractive in these cases because they provide a better chance to recover prior losses. Thus, the current holders who are in losses are less likely to sell these lottery stocks. In other words, the effective demand for lottery stocks is particularly high when average investors of these stocks are in losses, leading to especially large overvaluation of these assets. However, when investors face prior gains, their demand for lottery-like assets is not as strong, because they are not risk seeking or in need of breaking even. Instead, because of the high volatility of lottery-like stocks, investors with MA tend to dislike these stocks if they are risk averse in their gain region.

As a result, if arbitrage forces are limited, lottery-like stocks could be overvalued compared with nonlottery-like stocks among the stocks where investors face prior losses, leading to lower future returns than nonlottery-like stocks. By contrast, among the stocks where investors face capital gains, lottery features may not be associated with lower future returns. The correlation can even turn positive because investors with capital gains usually dislike the high volatility of lottery-like stocks. Thus, RDP together with MA can potentially account for the empirical findings documented in this paper. We provide a more detailed argument in Section 3. However, we acknowledge that the static argument here might not be valid in a dynamic setting, as shown in Barberis and Xiong (2009). Although developing a formal model in a dynamic setting to account for our empirical findings would be helpful, it is beyond the scope of this paper, and therefore, we leave it for future research.

A second possible explanation for our empirical findings is from a potential underreaction to news channel as documented in Zhang (2006). To see why, we take the failure probability as an example. Stocks with capital losses (low CGO) are likely to have experienced a series of bad news. If prices respond slowly to information (underreaction to news), stocks with low CGO tend to be overvalued on average. Moreover, this underreaction effect is likely to be more severe among firms with higher failure probability, because when there is more information uncertainty (related to failure probability), investors' behavioral biases are likely to be stronger (e.g., Daniel et al. 1998, 2001) and arbitrage forces tend to be more limited. Consequently, among the stocks with low CGO, those with higher failure probabilities are likely to be more overvalued, leading to lower future returns (a negative relationship between the failure probability and future returns). However, firms with capital gains (high CGO) have probably experienced good news and therefore have been underpriced because of the underreaction to news. Similarly, this underpricing effect should be stronger for firms with higher failure probabilities, leading to higher future returns. Thus, there is a positive relationship between the failure probability and future returns among firms with high CGO. To summarize, CGO is empirically related to news experienced in the past, whereas the lottery proxy is related to information uncertainty, which is likely to exacerbate the underreaction to news effect. Therefore, the underreaction to news channel could potentially generate the empirical return pattern that we document.

The third possible explanation is from the disposition effect-induced mispricing effect. One might argue that CGO itself is a proxy for mispricing as in Grinblatt and Han (2005). Because of the disposition effect (i.e., investors' tendency to sell securities with prices that have increased since purchase rather than those with prices that have dropped), firms with higher CGO experience greater selling pressure and thus, are underpriced. Because stocks with greater skewness, especially for firms close to default, tend to have higher arbitrage costs, the final mispricing effect should be stronger among these firms. Similar to the underreaction to news story, this disposition effect-induced mispricing effect can potentially induce a negative skewness-return relation among low-CGO firms and a positive skewness-return relation among high-CGO firms as in our empirical findings. Notice that the mechanism based on RDP is different from this mispricing story because RDP does not require CGO to be a proxy for mispricing. It only needs investors' demand for skewness depending on a reference point. In addition, the lottery measures reflect return skewness in the explanation based on RDP, whereas they are proxies for arbitrage risks for the story based on the mispricing effect.

To investigate the roles of these possible mechanisms in driving our empirical findings, we perform a series

have a strong preference for positive skewness, which drives up the prices of distressed stocks and leads to lower future returns. We construct this proxy as our fourth measure of the lottery feature using their logit model (12-month lag in table 4 of Campbell et al. 2008). The sample period of *Deathp* starts in January 1972 because of the availability of the quarterly Compustat data used in the calculation.

*Oscorep*: Finally, Ohlson (1980) develops a model to predict a firm's probability of bankruptcy from a set of accounting information. He finds that firms with a higher bankruptcy probability earn lower subsequent returns. Following his approach, we calculate firms' predicted bankruptcy probability based on the O-score (*Oscorep*; model 1 of table 4 of Ohlson 1980) and use this proxy as our fifth measure of the lottery feature.

All of the five variables above are associated with return skewness in the data, although they are motivated by different concepts in the original studies.[10] We will show that they exhibit another common feature: the anomalies related to these measures depend on whether CGO is positive or negative. Then we provide a unified framework to understand all of these lottery-related anomalies.

## 2.2. Summary Statistics and One-Way Sorts

This section reports summary statistics and the results for single-sorted portfolios. Then Section 2.3 studies the role of CGO in the lottery-related anomalies.

Table 1 presents summary statistics and the results when stocks are sorted on lottery proxies. At the end of month $t$, we sort stocks into quintiles based on CGO (panel A of Table 1) or one of the five lottery proxies (panel B of Table 1). In each quintile, the portfolio excess return $Ret^e$ is calculated as the value-weighted returns of individual stocks minus the one-month Treasury bill rate in month $t + 1$. The intercepts of the Fama–French three-factor regression for the value-weighted portfolios are denoted by $\alpha_{FF3}$. We also calculate other firm characteristics, such as the book-to-market value for each quintile. In these calculations, stocks are equally weighted. All firm characteristics are measured at the end of month $t$, with the only exception that ex post skewness is measured by return skewness over the next 12 months. All $t$ statistics (in parentheses) are based on the heteroskedasticity-consistent standard errors of White (1980) for portfolio returns and the standard errors of Newey and West (1987) with a lag of 36 for firm characteristics.

Panel A of Table 1 reports summary statistics for portfolios sorted on CGO using the measures from both Grinblatt and Han (2005) and Frazzini (2006). Consistent with the previous literature, high-CGO firms tend to have larger firm size, higher past returns, and lower return volatility than low-CGO firms. In particular, stocks with capital gains (high CGO) outperform stocks with capital losses (low CGO)cyTJ-3.522nmFolloilng mont1.e e12.1aed b68.4(e)83.6(r)4.1waen tedbo(t)4.1rom

**Table 1.** Summary Statistics

Panel A: VW excess returns and EW firm characteristics for five CGO portfolios

| | $Ret^e$ | $\alpha_{FF3}$ | CGO | LOGME | BM | $Ret_{-1}$ | $Ret_{-12,-1}$ | $Ret_{-36,-12}$ | RetVol | Turnover |
|---|---|---|---|---|---|---|---|---|---|---|
| CGO of Grinblatt and Han (2005) | | | | | | | | | | |
| CGO1 | 0.49 | −0.14 | −0.63 | 5.06 | 0.90 | −0.01 | −0.07 | 0.41 | 0.13 | 0.07 |
| CGO2 | 0.41 | −0.16 | −0.20 | 5.47 | 0.88 | 0.00 | 0.05 | 0.39 | 0.11 | 0.07 |
| CGO3 | 0.48 | −0.04 | −0.04 | 5.74 | 0.87 | 0.01 | 0.15 | 0.40 | 0.11 | 0.07 |
| CGO4 | 0.49 | 0.00 | 0.08 | 5.80 | 0.87 | 0.03 | 0.28 | 0.44 | 0.11 | 0.07 |
| CGO5 | 0.67 | 0.23 | 0.25 | 5.39 | 0.91 | 0.05 | 0.56 | 0.55 | 0.12 | 0.06 |
| P5 − P1 | 0.18 | 0.37 | 0.87 | 0.33 | 0.01 | 0.06 | 0.63 | 0.14 | −0.01 | −0.01 |
| *t*-Statistic | (1.01) | (2.06) | (14.77) | (1.87) | (0.22) | (12.68) | (18.76) | (2.55) | (−0.93) | (−2.09) |
| CGO of Frazzini (2006) | | | | | | | | | | |
| CGO1 | 0.80 | −0.09 | −0.66 | 5.42 | 0.76 | −0.03 | −0.07 | 0.57 | 0.14 | 0.11 |
| CGO2 | 0.59 | −0.15 | −0.15 | 5.81 | 0.77 | 0.00 | 0.08 | 0.45 | 0.12 | 0.08 |
| CGO3 | 0.66 | −0.02 | 0.02 | 6.05 | 0.78 | 0.01 | 0.17 | 0.43 | 0.11 | 0.08 |
| CGO4 | 0.61 | −0.02 | 0.15 | 6.20 | 0.77 | 0.03 | 0.30 | 0.47 | 0.11 | 0.08 |
| CGO5 | 0.88 | 0.30 | 0.36 | 5.93 | 0.80 | 0.07 | 0.60 | 0.55 | 0.13 | 0.09 |
| P5 − P1 | 0.08 | 0.39 | 1.01 | 0.51 | 0.04 | 0.10 | 0.67 | −0.02 | −0.01 | −0.01 |
| *t*-Statistic | (0.38) | (1.99) | (16.43) | (4.30) | (0.96) | (13.64) | (11.70) | (−0.20) | (−2.21) | (−2.56) |

Panel B: VW excess returns and EW ex post skewness for five lottery portfolios

| | *Maxret* | | | *Jackpotp* | | | *Skewexp* | | | *Deathp* | | | *Oscorep* | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Proxy* | $Ret^e$ | $\alpha_{FF3}$ | *ExpSkew* | $Ret^e$ | $\alpha_{FF3}$ | *ExpSkew* | $Ret^e$ | $\alpha_{FF3}$ | *ExpSkew* | $Ret^e$ | $\alpha_{FF3}$ | *ExpSkew* | $Ret^e$ | $\alpha_{FF3}$ | *ExpSkew* |
| P1 | 0.49 | 0.07 | 0.45 | 0.54 | 0.08 | 0.17 | 0.78 | 0.19 | 0.16 | 0.58 | 0.19 | 0.32 | 0.45 | 0.12 | 0.35 |
| P2 | 0.52 | 0.03 | 0.38 | 0.68 | 0.05 | 0.30 | 0.65 | 0.01 | 0.22 | 0.55 | 0.05 | 0.28 | 0.55 | 0.10 | 0.37 |
| P3 | 0.57 | 0.03 | 0.41 | 0.62 | −0.07 | 0.40 | 0.65 | −0.07 | 0.31 | 0.52 | −0.13 | 0.36 | 0.52 | −0.05 | 0.39 |
| P4 | 0.53 | −0.09 | 0.45 | 0.47 | −0.28 | 0.49 | 0.24 | −0.63 | 0.42 | 0.58 | −0.22 | 0.46 | 0.56 | −0.02 | 0.44 |
| P5 | 0.26 | −0.46 | 0.56 | 0.01 | −0.75 | 0.60 | 0.14 | −0.77 | 0.63 | 0.16 | −0.83 | 0.63 | 0.51 | −0.16 | 0.61 |
| P5 − P1 | −0.24 | −0.52 | 0.11 | −0.53 | −0.83 | 0.43 | −0.64 | −0.96 | 0.46 | −0.41 | −1.02 | 0.32 | 0.06 | −0.28 | 0.25 |
| *t*-Statistic | (−1.07) | (−3.74) | (2.74) | (−1.74) | (−5.44) | (13.29) | (−2.06) | (−3.70) | (16.55) | (−1.64) | (−5.00) | (11.02) | (0.42) | (−2.73) | (14.80) |

Panel C: Correlation matrix

| | $CGO^{GH}$ | $CGO^{FR}$ | *Maxret* | *Jackpotp* | *Skewexp* | *Deathp* | *Oscorep* | *RetVol* | *IVol* | $\beta$ |
|---|---|---|---|---|---|---|---|---|---|---|
| $CGO^{GH}$ | 1.00 | | | | | | | | | |
| $CGO^{FR}$ | 0.76 | 1.00 | | | | | | | | |
| *Maxret* | −0.09 | −0.10 | 1.00 | | | | | | | |
| *Jackpotp* | −0.17 | −0.24 | 0.54 | 1.00 | | | | | | |
| *Skewexp* | −0.18 | −0.20 | 0.29 | 0.60 | 1.00 | | | | | |
| *Deathp* | −0.38 | −0.42 | 0.25 | 0.44 | 0.36 | 1.00 | | | | |
| *Oscorep* | −0.02 | −0.02 | 0.19 | 0.30 | 0.24 | 0.44 | 1.00 | | | |
| *RetVol* | −0.07 | −0.12 | 0.49 | 0.62 | 0.36 | 0.21 | 0.29 | 1.00 | | |
| *IVol* | −0.18 | −0.20 | 0.84 | 0.67 | 0.37 | 0.36 | 0.23 | 0.56 | 1.00 | |
| $\beta$ | −0.09 | −0.11 | 0.29 | 0.25 | 0.03 | 0.07 | 0.07 | 0.66 | 0.31 | 1.00 |

expected, the correlations between each pair of the lottery proxies are all positive, ranging from 0.19 to 0.6, with the two default probability measures generally having a lower correlation with the other three variables. CGO measures are generally slightly negatively correlated with lottery measures, particularly for *Deathp*, *Skewexp*, and *Jackpotp*, where past return is an explicit input in construction of the variables. Not surprisingly, stocks with higher lottery features also tend to have higher volatility. In particular, the correlation between idiosyncratic volatility and *Maxret* is 0.84, which is consistent with the findings in Bali et al. (2011). We show later that our results on lottery features remain strong and robust after controlling for volatility measures using various parametric and nonparametric approaches.

### 2.3. Double Sorts

As shown in the preceding subsection, our five lottery measures unconditionally predict future returns in a way that is consistent with previous studies in the literature. We now examine to what extent these predictive patterns depend on stocks' previous capital gains or losses. At the end of month $t$, we independently sort stocks into quintiles based on CGO and one of our five lottery measures. We next track value-weighted portfolio returns in month $t + 1$.

Table 2 presents the double-sorting results based on the CGO of Grinblatt and Han (2005) and the five proxies for the lottery-like feature. Panel A of Table 2 reports excess returns for these portfolios, whereas panel B of Table 2 presents the Fama–French three-factor $\alpha$ values. Because of the independent sorting, we have a similar spread for the lottery proxy in the high-CGO group (CGO5) and the low-CGO group (CGO1). However, the future returns exhibit distinct patterns in these two groups. We take the maximum daily return in the last month (*Maxret*) as an exampl2.6(rturnsbfter)-401.8(previo)-9.5(u

**Table 2.** Double-Sorted Portfolio Returns by the CGO of Grinblatt and Han (2005) and Lottery Proxies

Panel A: Excess return

| | *Maxret* | | | | *Jackpotp* | | | | *Skewexp* | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Proxy* | CGO1 | CGO3 | CGO5 | C5 − C1 | CGO1 | CGO3 | CGO5 | C5 − C1 | CGO1 | CGO3 | CGO5 | C5 − C1 |
| P1 | 1.04 | 0.64 | 0.51 | | 0.80 | 0.59 | 0.60 | | 0.77 | 0.77 | 0.94 | |
| P3 | 0.59 | 0.48 | 0.81 | | 0.58 | 0.41 | 1.13 | | 0.58 | 0.64 | 0.96 | |
| P5 | −0.34 | 0.12 | 1.05 | | −0.37 | −0.12 | 1.29 | | −0.03 | −0.19 | 0.89 | |
| P5 − P1 | −1.38 | −0.52 | 0.54 | 1.92 | −1.16 | −0.71 | 0.69 | 1.86 | −0.80 | −0.96 | −0.05 | 0.75 |
| *t*-Statistic | (−5.35) | (−2.31) | (2.30) | (7.50) | (−4.15) | (−2.16) | (2.30) | (7.36) | (−2.29) | (−2.74) | (−0.22) | (2.23) |

| | *Deathp* | | | | *Oscorep* | | | |
|---|---|---|---|---|---|---|---|---|
| *Proxy* | CGO1 | CGO3 | CGO5 | C5 − C1 | CGO1 | CGO3 | CGO5 | C5 − C1 |
| P1 | 0.89 | 0.53 | 0.78 | | 0.66 | 0.48 | 0.63 | |
| P3 | 0.79 | 0.53 | 0.81 | | 0.58 | 0.40 | 0.71 | |
| P5 | −0.04 | 0.57 | 1.02 | | 0.04 | 0.40 | 1.16 | |
| P5 − P1 | −0.93 | 0.04 | 0.24 | 1.16 | −0.62 | −0.08 | 0.53 | 1.15 |
| *t*-Statistic | (−3.04) | (0.16) | (0.85) | (3.77) | (−2.81) | (−0.48) | (2.99) | (4.70) |

Panel B: FF3

| | *Maxret* | | | | *Jackpotp* | | | | *Skewexp* | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Proxy* | CGO1 | CGO3 | CGO5 | C5 − C1 | CGO1 | CGO3 | CGO5 | C5 − C1 | CGO1 | CGO3 | CGO5 | C5 − C1 |
| P1 | 0.52 | 0.16 | 0.10 | | 0.22 | 0.08 | 0.19 | | 0.02 | 0.13 | 0.40 | |
| P3 | −0.10 | −0.14 | 0.35 | | −0.31 | −0.33 | 0.55 | | −0.35 | −0.12 | 0.37 | |
| P5 | −1.24 | −0.60 | 0.45 | | −1.30 | −0.84 | 0.65 | | −1.07 | −1.07 | 0.16 | |
| P5 − P1 | −1.76 | −0.76 | 0.35 | 2.11 | −1.52 | −0.92 | 0.46 | 1.98 | −1.09 | −1.21 | −0.24 | 0.85 |
| *t*-Statistic | (−8.36) | (−4.53) | (1.92) | (8.17) | (−7.63) | (−4.42) | (2.32) | (7.45) | (−3.59) | (−3.99) | (−1.09) | (2.52) |

| | *Deathp* | | | | *Oscorep* | | | |
|---|---|---|---|---|---|---|---|---|
| *Proxy* | CGO1 | CGO3 | CGO5 | C5 − C1 | CGO1 | CGO3 | CGO5 | C5 − C1 |
| P1 | 0.47 | 0.05 | 0.40 | | 0.30 | 0.08 | 0.29 | |
| P3 | 0.11 | −0.14 | 0.17 | | −0.16 | −0.19 | 0.20 | |
| P5 | −1.12 | −0.41 | 0.19 | | −0.87 | −0.27 | 0.53 | |
| P5 − P1 | −1.59 | −0.46 | −0.21 | 1.38 | −1.17 | −0.35 | 0.24 | 1.41 |
| *t*-Statistic | (−5.98) | (−1.99) | (−0.83) | (4.36) | (−6.25) | (−2.35) | (1.55) | (5.90) |

*Notes.* At the beginning of every month, we independently sort stocks into five groups based on lagged CGO of Grinblatt and Han (2005) and five groups based on lagged lottery proxies (indicated by P1-P5). The portfolios are then held for the next month. We report the monthly value-weighted excess returns in Panel A and the intercepts of the Fama–French three-factor (FF3) regression in Panel B. The CGO of Grinblatt and Han (2005) at week *t* is computed the same way as in Table 1. Monthly CGO is weekly CGO of the last week in each month. *Maxret* is the maximum daily return in the last month, *Jackpotp* is the predicted jackpot probability in the last month from Conrad et al. (2014), *Skewexp* is the expected idiosyncratic skewness in the last month from Boyer et al. (2010), *Deathp* is the predicted failure probability in the last month from Campbell et al. (2008), and *Oscorep* is the predicted bankruptcy probability of default in the last month from Ohlson (1980). We only report the bottom-, middle-, and top-quintile CGO portfolios and their differences to save space. Excess returns and FF3 α values are reported in percentages. The sample period is from January 1965 to December 2014 for *Maxret* and *Oscorep*, from January 1972 to December 2014 for *Jackpotp* and *Deathp*, and from January 1988 to December 2014 for *Skewexp*. The *t*-statistics are calculated based on the heteroskedasticity-consistent standard errors of White (1980).

holds for the Fama–French three-factor $\alpha$ values, as shown in panel B of Table 2. More interestingly, panel B of Table 2 shows that, among low-CGO firms, a large bulk of the return spreads between low- and high-skewness firms is caused by the negative $\alpha$ of the lottery-like assets. Taking *Maxret* as an example, the long leg has an $\alpha$ of 0.52% per month, whereas the short leg has an $\alpha$ of −1.24% per month.[11] This is consistent with the notion that facing prior losses, the demand for lottery-like assets increases. Because of limits to arbitrage and especially, short-sale impediments, this excess demand drives up the price of lottery-like assets and leads to low subsequent returns for these assets.

In contrast to low-CGO firms, the lottery-like assets do not underperform the non-lottery-like assets among high-CGO firms. In fact, among high-CGO firms, the excess return spreads between the lottery-like stocks and the non-lottery-like stocks are 0.54%, 0.69%, −0.05%, 0.24%, and 0.53% per month for the five proxies, respectively. Four of these five return spreads are positive, and three of them are significant. The patterns are similar for the Fama–French three-factor

Next, we confirm that our results are not mainly driven by investors' reference-dependent preference for return volatility. Because high-skewness stocks are typically also more volatile, it is possible that the underperformance of lottery-like assets among firms with negative CGO is caused by investors' preference for volatility (rather than skewness) after losses. For example, prospect theory posits that investors are risk-seeking after losses, and thus, they might prefer stocks with high volatility after losses. Indeed, Wang et al. (2017) find a significant and negative risk–return relation among low-CGO stocks where investors face losses. To ensure that our results are not primarily being driven by investors' preference for volatility after losses, we reexamine the patterns on lottery portfolios by purging the confounding effect from volatility. We use both parametric and nonparametric methods to control for the volatility effect, and the results are shown in Table 8.

Panels A and B of Table 8 report double-sorted portfolio results based on CGO and residual lottery measures. In particular, at each month, we first run cross-sectional regressions of each of our five lottery proxies on monthly return volatility over the past five years, and then we use the residual lottery proxies to repeat our double-sorting exercises. Panel A of Table 8 reports results using *IVol*, and panel B of Table 8 reports results using *RetVol*. In panels C and D of Table 8, we do volatility-adjusted lottery sorts to further control for the potential nonlinear relation between volatility and lottery proxies. Specifically, we first sort all stocks into 10 deciles based on *IVol* (panel C of Table 8) or *RetVol* (panel D of Table 8); within each decile, we then divide stocks into five groups based on each one of the five lottery proxies, and finally, we collapse across the volatility groups. In this way, we obtain five volatility-adjusted lottery portfolios, and each portfolio contains stocks with a similar level of volatility. We then do double-sorting exercises based on CGO

**Table 8.** Residual Lottery Spreads

| | | *Maxret* | | | *Jackpotp* | | | *Skewexp* | | | *Deathp* | | | *Oscorep* | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Proxy* | | CGO1 | CGO5 | C5 – C1 | CGO1 | CGO5 | C5 – C1 | CGO1 | CGO5 | C5 – C1 | CGO1 | CGO5 | C5 – C1 | CGO1 | CGO5 | C5 – C1 |
| Panel A: Residual lottery spread, *IVol* | | | | | | | | | | | | | | | | |
| *Exret* | P5 – P1 | –0.79 | 0.12 | 0.92 | –0.63 | 0.70 | 1.33 | –0.40 | –0.06 | 0.34 | –0.49 | 0.14 | 0.63 | –0.11 | 0.18 | 0.29 |
| | *t*-Statistic | (–4.03) | (0.64) | (3.86) | (–2.57) | (2.92) | (5.41) | (–1.28) | (–0.23) | (1.02) | (–1.78) | (0.60) | (2.09) | (–0.55) | (1.01) | (1.20) |
| FF3 $\alpha$ | P5 – P1 | –0.87 | 0.13 | 1.00 | –0.91 | 0.51 | 1.42 | –0.60 | –0.24 | 0.36 | –1.00 | –0.24 | 0.76 | –0.42 | 0.00 | 0.42 |
| | *t* statistic | (–4.20) | (0.70) | (4.03) | (–4.57) | (2.77) | (5.34) | (–2.08) | (–1.04) | (1.03) | (–3.62) | (–1.1) | (2.36) | (–2.14) | (0.00) | (1.73) |
| Panel B: Residual lottery spread, *RetVol* | | | | | | | | | | | | | | | | |
| *Exret* | P5 – P1 | –0.92 | 0.10 | 1.02 | –0.68 | 0.54 | 1.21 | –0.68 | –0.05 | 0.63 | –0.60 | 0.17 | 0.77 | 0.05 | 0.02 | –0.03 |
| | *t*-Statistic | (–4.59) | (0.63) | (4.19) | (–2.99) | (2.62) | (4.81) | (–1.89) | (–0.18) | (1.82) | (–1.97) | (0.72) | (2.47) | (0.21) | (0.11) | (–0.11) |
| FF3 $\alpha$ | P5 – P1 | –1.02 | –0.02 | 0.99 | –0.91 | 0.28 | 1.19 | –0.80 | –0.17 | 0.63 | –1.19 | –0.19 | 1.00 | –0.20 | –0.15 | 0.05 |
| | *t*-Statistic | (–4.80) | (–0.14) | (3.96) | (–4.15) | (1.60) | (4.62) | (–2.57) | (–0.66) | (2.07) | (–4.07) | (–0.82) | (3.18) | (–0.97) | (–0.84) | (0.19) |
| Panel C: Volatility-adjusted lottery spread, *IVol* | | | | | | | | | | | | | | | | |
| *Exret* | P5 – P1 | –0.74 | –0.21 | 0.54 | –0.20 | 0.41 | 0.61 | –0.44 | 0.03 | 0.47 | –0.38 | –0.17 | 0.21 | –0.37 | 0.32 | 0.69 |
| | *t*-Statistic | (–5.11) | (–1.66) | (3.02) | (–1.15) | (2.35) | (3.52) | (–1.67) | (0.12) | (1.63) | (–1.94) | (–0.70) | (0.84) | (–1.77) | (1.69) | (3.32) |
| FF3 $\alpha$ | P5 – P1 | –0.77 | –0.15 | 0.62 | –0.38 | 0.18 | 0.56 | –0.49 | –0.06 | 0.43 | –0.83 | –0.47 | 0.36 | –0.75 | 0.10 | 0.85 |
| | *t*-Statistic | (–5.49) | (–1.19) | (3.34) | (–2.95) | (1.21) | (3.00) | (–1.96) | (–0.34) | (1.73) | (–4.86) | (–2.17) | (1.43) | (–3.75) | (0.58) | (3.79) |
| Panel D: Volatility-adjusted lottery spread, *RetVol* | | | | | | | | | | | | | | | | |
| *Exret* | P5 – P1 | –1.52 | –0.08 | 1.44 | –0.40 | 0.27 | 0.67 | –0.62 | 0.10 | 0.72 | –0.65 | –0.09 | 0.56 | –0.08 | 0.28 | 0.36 |
| | *t*-Statistic | (–10.51) | (–0.69) | (7.88) | (–2.18) | (1.47) | (3.42) | (–2.45) | (0.46) | (2.77) | (–2.97) | (–0.41) | (2.56) | (–0.45) | (1.78) | (2.09) |
| FF3 $\alpha$ | P5 – P1 | –1.55 | –0.18 | 1.37 | –0.55 | 0.09 | 0.64 | –0.53 | 0.13 | 0.66 | –1.10 | –0.40 | 0.70 | –0.44 | 0.13 | 0.56 |
| | *t*-Statistic | (–10.33) | (–1.32) | (7.32) | (–3.27) | (0.55) | (3.46) | (–2.15) | (0.72) | (2.68) | (–5.29) | (–2.13) | (3.34) | (–3.04) | (0.87) | (3.23) |

*Notes.* Panels A and B report the value-weighted excess returns and Fama–French three-factor (FF3) $\alpha$ values for residual lottery spreads (high minus low portfolio returns based on residual lottery measures) in the bottom- and top-quintile CGO groups and their differences. Twenty-five portfolios are constructed at the end of every month from independent sorts by the CGO of Grinblatt and Han (2005) and each of the five residual lottery proxies, which are the residuals obtained by regressing cross-sectionally each of the five lottery proxies on total return volatility (panel A) or idiosyncratic volatility (panel B). Panels C and D report the value-weighted excess returns and FF3 $\alpha$ values for lottery spreads based on volatility-adjusted lottery portfolios in the bottom- and top-quintile CGO groups and their differences. Specifically. we first sort all stocks into 10 deciles according to their total return volatility (panel C) or idiosyncratic volatility (panel D); within each decile, we then equally divide stocks into five groups according to each one of the five lottery proxies; and finally, we collapse across the volatility groups. In this way, we obtain five volatility-adjusted lottery portfolios; we interact them independently with five CGO quintiles and result in 25 portfolios. These portfolios are held for one month. *RetVol* is total return volatility, defined as the standard deviation of monthly returns over the past five years with a minimum of two years. *IVol* is idiosyncratic volatility, defined as the standard deviation of the residuals from the FF3 model using daily excess returns within a month with a minimum of 10 nonmissing observations. We consider five lottery proxies: *Maxret* is the maximum daily return in the last month, *Jackpotp* is the predicted jackpot probability in the last month from Conrad et al. (2014), *Skewexp* is the expected idiosyncratic skewness in the last month from Boyer et al. (2010), *Deathp* is the predicted failure probability in the last month from Campbell et al. (2008), and *Oscorep* is the predicted bankruptcy probability in the last month from Ohlson (1980). Returns and $\alpha$ values are reported in percentages. The sample period is from January 1965 to December 2014 for *Maxret* and *Oscorep*, from January 1972 to December 2014 for *Jackpotp* and *Deathp*, and from January 1988 to December 2014 for *Skewexp*. The *t*-statistics are calculated based on the heteroskedasticity-consistent standard errors of White (1980).

**Table 10.** Double Sorts in Subsamples of Top and Bottom Institutional Ownership or Nominal Stock Price

| | Top 25% IO | | | Bottom 25% IO | | | Top − bottom IO | | |
|---|---|---|---|---|---|---|---|---|---|
| Lottery proxy | CGO1 | CGO5 | C5 − C1 | CGO1 | CGO5 | C5 − C1 | CGO1 | CGO5 | C5 − C1 |
| *Maxret* | −0.94 | 0.21 | 1.15 | −2.43 | −0.22 | 2.21 | 1.49 | 0.43 | −1.06 |
| | (−3.48) | (0.67) | (3.65) | (−8.58) | (−0.68) | (5.15) | (4.23) | (1.15) | (−2.00) |
| *Jackpotp* | −0.79 | −0.22 | 0.57 | −2.17 | −0.19 | 1.97 | 1.38 | −0.02 | −1.40 |
| | (−3.32) | (−0.92) | (1.83) | (−5.56) | (−0.57) | (3.92) | (3.06) | (−0.06) | (−2.37) |
| *Skewexp* | −0.79 | −0.63 | 0.15 | −1.74 | 0.42 | 2.17 | 0.96 | −1.06 | −2.01 |
| | (−2.39) | (−2.25) | (0.42) | (−4.92) | (1.37) | (4.84) | (2.14) | (−2.46) | (−3.52) |
| *Deathp* | −0.90 | −0.52 | 0.38 | −1.78 | −0.90 | 0.88 | 0.88 | 0.38 | −0.49 |
| | (−2.95) | (−1.81) | (1.07) | (−4.52) | (−2.10) | (1.68) | (1.89) | (0.74) | (−0.79) |
| *Oscorep* | −0.42 | 0.09 | 0.50 | −1.65 | 0.25 | 1.90 | 1.23 | −0.16 | −1.39 |
| | (−1.54) | (0.45) | (1.68) | (−4.07) | (0.84) | (4.30) | (2.59) | (−0.45) | (−2.68) |

| | Top 25% price | | | Bottom 25% price | | | Top − bottom price | | |
|---|---|---|---|---|---|---|---|---|---|
| Lottery proxy | CGO1 | CGO5 | C5 − C1 | CGO1 | CGO5 | C5 − C1 | CGO1 | CGO5 | C5 − C1 |
| *Maxret* | −0.46 | 0.62 | 1.08 | −3.00 | −1.11 | 1.88 | 2.54 | 1.73 | −0.81 |
| | (−2.30) | (3.07) | (4.61) | (−9.5) | (−4.13) | (5.00) | (7.84) | (5.64) | (−1.98) |
| *Jackpotp* | −0.42 | 0.50 | 0.92 | −1.69 | −0.37 | 1.32 | 1.27 | 0.87 | −0.40 |
| | (−1.99) | (2.60) | (3.74) | (−5.34) | (−1.09) | (3.22) | (3.61) | (2.33) | (−0.87) |
| *Skewexp* | −0.86 | −0.90 | −0.05 | −1.00 | 0.51 | 1.51 | 0.14 | −1.42 | −1.56 |
| | (−2.85) | (−3.77) | (−0.15) | (−2.45) | (1.45) | (2.90) | (0.30) | (−3.79) | (−2.74) |
| *Deathp* | −0.61 | −0.39 | 0.21 | −1.91 | −1.09 | 0.82 | 1.31 | 0.70 | −0.61 |
| | (−2.74) | (−1.85) | (0.84) | (−5.84) | (−3.21) | (1.82) | (3.65) | (1.79) | (−1.27) |
| *Oscorep* | −0.30 | 0.09 | 0.40 | −1.72 | −0.46 | 1.26 | 1.41 | 0.55 | −0.86 |
| | (−1.77) | (0.54) | (1.77) | (−5.93) | (−1.86) | (3.52) | (4.23) | (1.91) | (−2.10) |

*Notes.* This table reports the Fama–French three-factor monthly $\alpha$ values (in percentages) for the lottery spread (difference between top- and bottom-quintile lottery portfolios) among the bottom- and top-tercile CGO portfolios and their differences within top 25% institutional ownership (IO; or nominal stock price) and bottom 25% IO (or nominal stock price) stocks. At the beginning of every month, we first divide stocks into three groups (top 25%, middle 50%, and bottom 25%) by IO (or price), and within each subgroup, stocks are further independently sorted into three groups based on the lagged CGO of Grinblatt and Han (2005) and five groups based on lagged lottery proxies. The portfolio is then held for one month. IO is the percentage of shares held by institutions each month. The CGO of Grinblatt and Han (2005) at week $t$ is computed as one less the ratio of the beginning of the week $t$ reference price to the end of week $t-1$ price. The week $t$ reference price is the average cost basis calculated as $RP_t = k^{-1}\sum_{n=1}^{T}\left(V_{t-n}\prod_{\tau=1}^{n-1}(1-V_{t-n-\tau})\right)P_{t-n}$, where $V_t$ is week $t$'s turnover in the stock, $T$ is the number of weeks in the previous five years, and $k$ is a constant that makes the weights on past prices sum to one. Turnover is calculated as trading volume divided by number of shares outstanding. Monthly CGO is weekly CGO of the last week in each month. We consider five lottery proxies: *Maxret* is the maximum daily return in the last month, *Jackpotp* is the predicted jackpot probability in the last month from Conrad et al. (2014), *Skewexp* is the expected idiosyncratic skewness in the last month from Boyer et al. (2010), *Deathp* is the predicted failure probability in the last month from Campbell et al. (2008), and *Oscorep* is the predicted bankruptcy probability in the last month from Ohlson (1980). In the cases of IO portfolios, the sample period is from January 1980 to October 2014 for *Maxret*, *Oscorep*, *Jackpotp*, and *Deathp* and from January 1988 to October 2014 for *Skewexp*. In the cases of price portfolios, the sample period is from January 1965 to December 2014 for *Maxret* and *Oscorep*, from January 1972 to December 2014 for *Jackpotp* and *Deathp*, and from January 1988 to December 2014 for *Skewexp*. The $t$-statistics in parentheses are calculated based on the heteroskedasticity-consistent standard errors of White (1980).

with CRSP share codes corresponding to 10 and 11 and apply filters from Frazzini (2006) to exclude erroneous observations.[26] Observations are at the fund/stock/report day level, where funds typically report their holdings at a quarterly frequency. Following this literature, we assume that trading happens on the report date.

We perform probit regressions of a selling indicator on investors' gains and losses ($Ret^+$ and $Ret^-$), the lottery feature of a stock, and the interaction between these two as well as other controls. We use the five lottery measures elaborated in the preceding section to proxy for the lottery feature of a stock. For both retail investors and mutual funds trading, we adopt a first-in-first-out assumption in calculating investors' return since purchase. If an investor has made several purchases at various points, we take a weighted average of purchase prices, where the weight equals the percentage of shares bought at that time that are still held by the investor. The terms $Ret^+$ and $Ret^-$ are the positive and negative parts of the return since purchase, respectively ($Ret^+ = \text{Max}\{Ret, 0\}$ and $Ret^- = \text{Min}\{Ret, 0\}$).

The terms $Proxy \times Ret^+$ and $Proxy \times Ret^-$ are the interaction terms of the lottery feature and gains and losses, where proxy stands for one of these lottery measures. Other control variables include an indicator that equals 1 if $Ret$ is positive and 0 otherwise ($I(Ret > 0)$), an indicator that equals 1 if $Ret$ is 0 and 0 otherwise ($I(Ret = 0)$), return volatility calculated from the daily returns in the past one year ($RetVol$), the logarithm of

**Table 11.** Propensity to Sell Lottery Stocks, Individual Investors

| | *I*(Selling) | | | | |
|---|---|---|---|---|---|
| *Proxy* | *Maxret* | *Jackpotp* | *Skewexp* | *Deathp* | *Oscorep* |
| $Ret^+$ | 0.0007 | 0.0005 | 0.0004 | 0.0005 | 0.0009 |
| | (4.90) | (4.60) | (3.43) | (5.03) | (8.98) |
| $Ret^-$ | −0.0028 | −0.0012 | −0.0011 | −0.0013 | −0.0004 |
| | (−16.97) | (−8.04) | (−5.56) | (−7.99) | (−3.00) |
| *Proxy* | 0.0088 | −0.0400 | −0.0010 | −0.3593 | −0.0020 |
| | (14.14) | (−6.51) | (−11.44) | (−7.12) | (−6.12) |
| $Ret^+ \times Proxy$ | 0.0038 | 0.0615 | 0.0013 | 0.9305 | 0.0049 |
| | (2.10) | (5.38) | (5.78) | (7.62) | (5.55) |
| $Ret^- \times Proxy$ | 0.0367 | 0.0924 | 0.0015 | 0.9433 | 0.0048 |
| | (18.93) | (7.59) | (5.37) | (7.81) | (5.00) |
| *RetVol* | 0.0431 | 0.0689 | 0.0528 | 0.0583 | 0.0578 |
| | (20.75) | (26.96) | (24.94) | (25.02) | (24.26) |
| log(buy price) | 0.0005 | 0.0003 | 0.0002 | 0.0003 | 0.0004 |
| | (10.84) | (7.52) | (5.80) | (8.48) | (9.39) |
| sqrt(time owned) | −0.0001 | −0.0001 | −0.0001 | −0.0001 | −0.0001 |
| | (−38.62) | (−38.37) | (−39.03) | (−39.20) | (−38.96) |
| $I(Ret > 0)$ | 0.0010 | 0.0010 | 0.0010 | 0.0010 | 0.0010 |
| | (17.47) | (18.25) | (17.73) | (17.89) | (17.36) |
| $I(Ret = 0)$ | −0.0001 | −0.0000 | −0.0001 | −0.0000 | −0.0001 |
| | (−1.32) | (−0.23) | (−0.63) | (−0.35) | (−0.79) |
| Observations | 25,615,232 | 23,827,309 | 25,524,756 | 25,439,907 | 22,632,746 |
| Pseudo-$R^2$ | 0.0420 | 0.0419 | 0.0421 | 0.0420 | 0.0420 |

*Notes.* This table presents results from probit regressions in which the dependent variable is a dummy equal to one if a stock was sold and zero otherwise. The coefficients reflect the marginal effect on the average stock selling behavior of individual investors. The data set contains the daily holdings of 10,000 retail investors who are randomly selected from 78,000 households with brokerage accounts at a large discount broker from January 1991 to December 1996. Observations are at the investor/stock/day level. The same data set is used in Barber and Odean (2000, 2001, 2002) and, more recently, in Ben-David and Hirshleifer (2012). $Ret^+$ ($Ret^-$) is the return since purchase if the return since purchase is positive (negative) and zero otherwise. Return since purchase is defined as the difference between current price and purchase price divided by purchase price (or weighted average price in the case of multiple purchases). The current price is the selling price, price of buying additional shares, or end-of-day price each day. $I_{Ret>0}$ ($I_{Ret=0}$) is a dummy equal to one if the return since purchase is positive (zero) and zero otherwise. *RetVol* is the total volatility of the daily stock returns over the past year. Log(buy price) is the log of purchase price in dollars. Sqrt(time owned) is the square root of the number of days since purchase. We consider five lottery proxies: *Maxret* is the maximum daily return in the last month, *Jackpotp* is the predicted jackpot probability in the last month from Conrad et al. (2014), *Skewexp* is the expected idiosyncratic skewness in the last month from Boyer et al. (2010), *Deathp* is the predicted failure probability in the last month from Campbell et al. (2008), and *Oscorep* is the predicted bankruptcy probability in the last month from Ohlson (1980). Standard errors are clustered at the investor level, and *t*-statistics are in parentheses.

purchase price (log(*BuyPrice*)), and the square root of the time since purchase (sqrt(*TimeOwned*), where time is measured in units of trading days for retail investors and months for mutual fund managers).

The timing of our regressions is designed as follows. First, all lottery proxies are calculated at a monthly frequency. For retail investors, the selling indicator on one day is regressed on the lottery proxy measured at the end of the previous month. For mutual fund trading, because typical funds report their holdings on a quarterly basis, trading reported at month end $t$ can actually happen from the beginning of month $t-2$ to the end of month $t$. To have lottery information available at the time of trading, we lag the lottery measure by three months: that is, using a lottery proxy at month end $t-3$ for the selling indicator at month end $t$.

Tables 11 and 12 present selling regression results for retail investors and mutual funds, respectively. The coefficients for the interaction terms are usually positive and significant, especially for $Proxy \times Ret^-$. This finding implies that investors' preference for lottery-like assets over non-lottery-like assets is significantly stronger in the loss region compared than in the gain region. This pattern generally holds for both retail investors and mutual fund managers, and it is robust to our five measures of lottery. This confirms our conjecture about the role of reference points in an investor's preference for lottery-like assets.

## 4. Conclusion

In this paper, we document that the return spreads between lottery-like assets and non-lottery-like assets

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## Endnotes

[1] The probability weighting over extreme events has been applied to understand many phenomena in finance, economics, and insurance. For a recent review, see Barberis (2013).

[2] Bali et al. (2011, 2017) also argue that the preference for lottery can account for the puzzle that firms with low volatility and low $\beta$ tend to earn higher returns.

[3] To clarify, our results do not exclude the existence of overweighting small-probability events. In fact, we find that the negative skewness–return relation is generally significant among stocks around the zero-CGO region, which supports an independent role for probability weighting in the lottery-related anomalies.

[4] In a two-period setting with a cumulative prospect theory preference but without MA, Barberis and Huang (2008) show that the CAPM still holds under assumptions, such as multivariate normal distribution for security payoffs. When there is a violation of these assumptions (e.g., MA or the multivariate normality assumption for security payoffs), the CAPM typically fails.

[5] Several studies also apply the reference-dependent feature in decision making to understand various other empirical findings in financial data. See Baker et al. (2012) for information on merger/acquisitions, George and Hwang (2004) and Li and Yu (2012) for information on the predictive power of 52-week high prices, and Dougal et al. (2015) for information on the credit spread.

[6] Our approach is reminiscent of the studies on habit formation. Campbell and Cochrane (1999) show that external habit formation can help account for the equity premium puzzle. In the following studies, Wachter (2006) and Verdelhan (2010) find that the same mechanism can account for the bond return predictability and the forward premium puzzle, respectively. These subsequent studies thus further validate the role of habit formation on asset price dynamics.

[7] For details, see equations 9 and 11 in Grinblatt and Han (2005).

[8] See equations 1 and 2 in Frazzini (2006) for details.

[9] Although our prior is that the lottery preference should be stronger among retail investors, as documented in Kumar (2009), this preference does not have to be confined to retail investors. A growing literature has shown that mutual fund managers exhibit many behavioral biases just like retail investors do. For instance, they exhibit the disposition effect (Frazzini 2006, An and Argyle 2017) and the rank effect (Hartzmark 2015), and they have rolling mental accounts (Frydman et al. 2018). Even professional traders have exhibited loss aversion (Coval and Shumway 2005). DeVault et al. (2019) argue that many institutional investors could be sentiment traders. Agarwal et al. (2018) show that mutual funds that are smaller and younger with poorer recent performance and more retail clientele tend to hold more lottery stocks, which could be associated with incentives to attract capital.

[10] *Deathp* and *Oscorep* are initially motivated to study firms' distress risk. Serving as a proxy for lottery feature is one interpretation among many that have been put forth to explain the negative relation between these measures and future returns.

[11] Related to this finding, Stambaugh et al. (2012) find that many anomalies are driven by the abnormally low returns from their short legs, especially after high-sentiment periods. They argue that this evidence is consistent with the notion that overpricing is more prevalent than underpricing because of short-sale impediments.

[12] In a recent study, Jiang et al. (2016) use different measures of skewness, and they also find that the negative return spread between firms with low and high skewness is more pronounced among firms with low CGO than among firms with high CGO.

[13] We thank the referee for encouraging us to investigate this positive $\alpha$ among high-CGO firms.

[14] Recently, Belo et al. (2014) also emphasized the importance of reporting both equal- and value-weighted portfolio returns.

[15] Another feature of prospect theory is that investors tend to overweight small-probability events. The asset pricing implications of probability weighting have been studied recently by Barberis and Huang (2008), Bali et al. (2011), Green and Hwang (2012), and Barberis et al. (2016), among others.

[16] See, for example, Shefrin and Statman (1985), Benartzi and Thaler (1995), Odean (1998), Barberis et al. (2001), Grinblatt and Han (2005), Frazzini (2006), and Barberis and Xiong (2012), among others.

[17] Once again, we acknowledge that our static argument above may not be valid in a dynamic setting, as shown by Barberis and Xiong (2009). Thus, before fully embracing our argument, one should develop a fully dynamic model, which is beyond the scope of our study. See Li and Yang (2013) for such a related dynamic model.

[18] We thank Terry Odean for the brokerage data.

[19] However, by exploring crosscountry variation in creditor protection, Gao et al. (2017) argue that shareholder expropriation is unlikely to account for the distress anomaly.

[20] For recent evidence on how risk attitude is affected by realized versus unrealized profits, see Imas (2016).

[21] In Table IA7 in Online Appendix II, we show that our results remain similar when we replace past returns with other proxies for news, including the most recent available standardized unexpected earnings, and cumulative abnormal returns around the most recent earnings announcement.

[22] For example, Avramov et al. (2013) show that many anomalies are only significant among distressed firms, suggesting that distressed firms are more difficult to arbitrage.

[23] One could use the nominal price level as another proxy for the lottery feature, as in Kumar (2009). Indeed, in untabulated analysis, we find that our results hold well when the nominal price is used as a lottery proxy.

[24] Recently, in a related paper, Lin and Liu (2016) find that the lottery-related anomalies are more pronounced among firms with stronger individual demand.

[25] Because of computational limitations, randomly selecting a sample of 10,000 is a general convention among studies using this data set. See, for example, Odean (1998) and Ben-David and Hirshleifer (2012).

[26] Observations are excluded if (1) the number of shares in a fund's portfolio is greater than the total number of shares outstanding in that stock, (2) the value of the fund holding of one stock is greater than the total asset value of the fund, (3) the stock has zero shares outstanding, and (4) the value of a fund reported by Thomson Reuters is different from the implied CRSP value by more than 100%.

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