The Role of Psychological Barriers in Lottery-Related Anomalies

Suk-Joon Byun*, Jihoon Goh**

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Abstract

Previous studies find that stocks with lottery features are overpriced. We show that anomalies induced by investors' lottery preferences exist primarily among stocks that are far from their 52-week high prices. The results suggest that if stocks are near their 52-week highs, investors no longer prefer lottery stocks since they consider the 52-week high a psychological barrier or an upper bound for prices. We find that the dependency between lottery-related anomalies and nearness to the 52-week high is pronounced among stocks with low institutional ownership. Alternative explanations, such as limits to arbitrage and capital gains, do not explain our results.

JEL Classification: G11, G12, G14

Keywords: prospect theory, lottery, skewness, psychological barrier, 52-week high, anchoring bias

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* College of Business, Korea Advanced Institute of Science and Technology, 85 Hoegiro, Dongdaemoon-gu, Seoul, 02455, Republic of Korea; Tel: +82 2 958 3552; E-mail: sjbyun@business.kaist.ac.kr

**(Corresponding author) College of Business, Korea Advanced Institute of Science and Technology, 85 Hoegiro, Dongdaemoon-gu, Seoul, 02455, Republic of Korea; Tel: +82 2 958 3968; E-mail: jihoonall@business.kaist.ac.kr

1. Introduction

Previous studies find that stocks with lottery-like payoffs have negative abnormal returns compared to stocks with non-lottery-like payoffs. In recent years, this has become one of the most widely studied anomalies in finance literature. Theoretically, Barberis and Huang (2008) explain this anomaly by the implications of cumulative prospect theory (Tversky and Kahneman, 1992).[1] The authors assert that investors could prefer stocks with positive skewness. This is because investors overweight the right tail probability, that is, the probability of extreme positive returns. Thus, stocks with lottery features are overpriced and have negative abnormal returns. Kumar (2009) empirically shows that individual investors prefer stocks with lottery-like payoffs; therefore, these stocks are overpriced. Many empirical papers use different measures for lottery features and find that lottery stocks have negative expected returns.[2]

Another well-documented literature related to investor preference concerns the 52-week high price. Numerous papers document that 52-week highs affect investor behavior. Kahneman and Tversky (1975) assert that people form estimates based on some initial value (anchor) and adjust from this anchor. This adjustment is insufficient since people anchor excessively. George and Hwang (2004) find that the 52-week high price explains the profits from momentum strategy because investors anchor to the 52-week high. The authors argue that a stock near its 52-week high is underpriced and has a positive expected return. Many studies examine the anchoring effect of the 52-week high in financial markets.[3] Birru (2015) finds that investors consider the 52-week high an upper bound for prices or a psychological barrier.

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[1] Brunnermeier, Gollier, and Parker (2007) explain preferences for lottery stocks by the optimal beliefs theory.

[2] Bali, Cakici, and Whitelaw (2011) use the maximum daily return over the previous one month, and Boyer, Mitton, and Vorkink (2010) use expected idiosyncratic skewness to measure lottery features. Conrad, Dittmar, and Ghysels (2013) and Xing, Zhang, and Zhao (2010) use option data to select stocks with lottery-like payoffs. Moreover, An, Wang, Wang, and Yu (2017) and Hur and Singh (2017) find the role of reference-dependent preferences and investor attention in lottery-related anomalies, respectively.

[3] The list of papers is Heath, Huddart, and Lang (1999), Grinblatt and Keloharju (2001), Baker, Pan, and Wurgler (2012), Li and Yu (2012), and Li, Lin, and Lin (2016). Hao, Chou, and Ko (2014) find the role of investor sentiment, and Bhootra and Hur (2013) find the role of recency bias in anchoring bias.

In this paper, we combine these two strands of literature on investor preference. We show that anomalies induced by lottery preference depend on the relative price to the 52-week high. Negative profits of lottery-related anomalies are pronounced among stocks far from 52-week highs. Why, then, is there an interaction between the 52-week high price and returns for lottery-related anomalies? We consider the role of psychological barriers in the lottery preferences of investors. Birru (2015) argues that the 52-week high serves as a psychological barrier, and investors consider this an upper bound for prices. In other words, if a stock price is near its 52-week high, investors expect that the stock price would not exceed the 52-week high. Thus, investors do not overweight the right tail probability of the stock, since they expect that there is no right tail above its 52-week high. Therefore, investors hesitate to buy lottery stocks near the 52-week highs, and they no longer prefer these stocks. This leads to the absence of lottery-related anomalies among stocks near 52-week highs. On the other hand, for a stock far from its 52-week high, investors anchor on the 52-week high and consider there to be room for the price to run up. Thus, investors overestimate the probability of extreme positive returns and prefer stocks with lottery features among stocks far from 52-week highs. Therefore, lottery-related anomalies are strong among these stocks.

We empirically test our explanation in several ways. First, we double-sort stocks into portfolios based on the nearness to 52-week highs (NH) and our main lottery measure. We use the maximum daily returns over the previous month (MAX) as our main lottery measure following Bali et al. (2011). The MAX effect is negative and strongly significant among stocks far from 52-week highs. However, this effect vanishes among stocks near 52-week highs. The difference in the MAX strategy profits between the top and bottom NH quintile portfolios is positively significant. We repeat our analyses using other lottery definitions in addition to MAX. Our alternative lottery measures are lottery stock index (LIDX) as in Han and Kumar (2013), jackpot probability (JPP) as in Conrad, Kapadia, and Xing (2014), and expected idiosyncratic skewness (ESKEW) as in Boyer et al. (2010). The differences in the profits of lottery-related anomalies between the top and bottom NH quintile portfolios are positively significant for all lottery definitions.[4]

Second, we show that the interactions between NH and lottery measures are stronger among stocks with lower institutional ownership (IO) than high IO stocks. Many papers support the theory that individual investors are more prone to behavioral biases than institutional investors (Odean, 1998; Barber and Odean, 2000, 2008; and Kumar, 2009). Thus, individual investors, rather than institutional investors, are more likely to consider a 52-week high a psychological barrier. To test this, we conduct double-sort analyses in subsamples based on IO. For each of our four lottery measures (MAX, LIDX, JPP, and ESKEW), we calculate the differences in the profits of lottery-related anomalies among high IO stocks (top 25%) and low IO stocks (bottom 25%). We find that the difference among low IO stocks is significantly greater than the difference among high IO stocks.[5]

Third, Fama and MacBeth (1973) regression results also indicate that lottery-related anomalies exist primarily among stocks far from 52-week highs. For each lottery proxy, we run a Fama and MacBeth (1973) regression of the stock return on the lagged independent variables including the interaction term between NH and each lottery proxy. The average coefficients for the interaction terms are positive and both statistically and economically significant for all lottery measures.

Next, we consider five alternative explanations, and we show that these are less supportive than our explanation based on the 52-week high. First, anomalies, including those that are lottery-related are pronounced among stocks with greater arbitrage risk since there is more mispricing of these stocks.[6] Stocks far from the 52-week high tend to have greater limits to arbitrage since their size is small and their price is low. Thus, our results might be driven by the effect of arbitrage risk. However, through triple-sort analysis, we show that our explanation is more supportive than this explanation. The interaction between NH and MAX is significant even after we control for size or stock price. Conversely,

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4 Our empirical results are robust to various sample selections, alternative NH measures, and the consideration of other stock characteristics.

5 We replace IO with residual IO and do the same analyses. We cross-sectionally regress IO on size to obtain the residual IO.

6 Many studies document limits to arbitrage and mispricing (De Long, Shleifer, Summers, and Waldmann, 1990; Shlefer and Vishny, 1997; and Mitchell, Pulvino, and Stafford, 2002). Ali, Hwang, and Trombley (2003) and Mendenhall (2004) document that anomalies are pronounced among stocks with high arbitrage risk.

if we control for NH, the interaction between MAX and size, or between MAX and price, is weak.

Second, An et al. (2017) document that lottery-related anomalies are dependent on capital gains overhang (CGO) by Grinblatt and Han (2005). The authors explain that investors have reference-dependent preferences; investors prefer lottery stocks when they have lost money rather than when they have gained profits. Since our NH measure is correlated with CGO, it might be possible that when stocks are near the 52-week high, investors do not prefer lottery stocks because they have gained profits, not because they have psychological barriers. However, similarly, we show that our explanation is more supportive than this explanation through triple-sort analysis.

The third possible alternative explanation is underreaction to new information (Zhang, 2006). Zhang (2006) argues that price continuation is due to behavioral biases, and this drift should be greater for stocks with greater information uncertainty. Since high MAX stocks tend to have greater uncertainty, high MAX stocks exhibit high returns among stocks with good news while they exhibit low returns among stocks with bad news. This leads to a weaker MAX effect among good news stocks compared to bad news stocks. We can use past returns (previous 11-month returns with a one-month lag) by Jegadeesh and Titman (1993) as a proxy for new information, and they correlate with our NH measure. Therefore, our results might be from this underreaction effect. However, similarly, we show that our explanation is more promising than the explanation through triple-sort analysis.

Fourth, Mbanga (2015) asserts that investors underreact to bad news particularly when stocks are far from the 52-week high and idiosyncratic volatility (IVOL) can be a proxy for bad news. Thus, the IVOL effect documented by Ang, Hodrick, Xing, and Zhang (2006) is stronger among stocks far from the 52-week high. Since IVOL and MAX are highly correlated, the IVOL effect might drive our result that the MAX effect is stronger among those stocks. To support our explanation as a more promising explanation, we conduct a double-sort analysis based on NH and residual MAX.[7] As with the previous results, the residual MAX effect is pronounced among stocks far from their 52-week highs.

[7] We cross-sectionally regress MAX on IVOL to obtain residual MAX and regress IVOl on MAX to obtain residual IVOL.

Conversely, we conduct a double-sort analysis based on NH and residual IVOL. We find that the interaction between NH and residual IVOL is reversed, which contradicts the prediction from the fourth explanation.

Lastly, we consider the effect of liquidity provision.[8] It is possible that a high MAX stock near its 52-week high has greater selling pressure from liquidity providers and the reversal would be smaller.[9] Moreover, past winner stocks are more likely to be liquid so that the reversal is smaller. Since the effect of liquidity is concentrated at the beginning of the month, we exclude the first five days of the month to remove this effect.[10] We find similar results as our previous results, which indicates that the liquidity effect does not drive our results.

Our research has several contributions to the literature. First, we find that the lottery preference of investors depends on the 52-week high that can serve as the psychological barrier or the anchor. Thus, the magnitude of lottery-related anomalies varies with the nearness to the 52-week high. To our knowledge, this is the first study to connect psychological barriers and lottery preference. Second, this paper explains the 52-week high effect on investor behavior using the belief-based explanation. The 52-week high price can serve as a psychological barrier or an upper bound for prices. Thus, for a stock near its 52-week high, investors do not believe the right tail probability or extreme positive returns above the 52-week high. This belief-based explanation is consistent with Birru (2015).

The remainder of our paper is organized as follows. Section 2 discusses our data, sample, and variable descriptions. Section 3 provides empirical results that support our explanations. Section 3 also provides alternative explanations and robustness tests, and Section 4 concludes.

[8] Many papers document the role of liquidity provision on short-term reversals (Nagel, 2012; Kaniel, Saar, and Titman, 2008; and Hameed and Mian, 2015).

[9] Cheng, Hameed, Subrahmanyam, and Titman (2016) show that past winner stocks have more liquidity providers so that monthly reversals are smaller among these stocks than past loser stocks.

[10] Our methodology is the same as the methodology in Hur and Singh (2017).

2. Data and Variables

In our research, we use data composed of common stocks listed on the NYSE, AMEX, or NASDAQ with share code 10 or 11. Stock data are from the Center for Research in Security Prices (CRSP) data set, and accounting data are from the Compustat data set. Our sample period is from July 1963 to December 2016. To reduce microstructure effects from penny stocks, we exclude stocks with prices below $5 at the end of each month. We also use the Thomson Reuters Institutional Holdings (13F) data set to calculate institutional ownership for each stock. For analyses using institutional ownership data, our sample period is from 1980 to 2016.

Our first main variable is a measure for the lottery feature. We use maximum daily returns over the previous month (MAX) following Bali et al. (2011). MAX of firm i at the end of the month t is

$$MAX_{i,t} = \max(R_{i,d}), \quad d \in \{1, \cdots, D_{i,t}\} \tag{1}$$

where $R_{i,d}$ is the return of stock i on day d and $D_{i,t}$ is the number of trading days in month t.

We use three alternative lottery measures. They are lottery stock index (LIDX) as in Han and Kumar (2013), jackpot probability (JPP) as in Conrad et al. (2014), and expected idiosyncratic skewness (ESKEW) as in Boyer et al. (2010).[11] For analyses using JPP, our sample period is from July 1972 to December 2016 following Conrad et al. (2014), and for analyses using ESKEW, our sample period is from January 1988 to December 2016 following Boyer et al. (2010).

Our second main variable is the nearness to the 52-week high price (NH). This measure represents a ratio of the current price to the 52-week high price. NH of firm i at the end of the month t is

$$NH_{i,t} = PRC_{i,t}/52HIGH_{i,t}, \tag{2}$$

where $PRC_{i,t}$ is the price of stock i at the end of the month t, and $52HIGH_{i,t}$ is the highest daily closing price from the beginning of the month $t-11$ to the end of the month t. Other variable

[11] For details of LIDX, see the definition of LOTT in the description of Table 1 on page 383 in Han and Kumar (2013). For details of JPP, see Equation (1) on page 460 in Conrad et al. (2014). For details of ESKEW, see Equation (1) and (2) on page 174, Equation (3) on page 175, and Equation (4) on page 176 in Boyer et al. (2010).

definitions are shown in the Appendix.

3. The 52-Week High and Lottery Preference

In this section, we empirically show that lottery-related anomalies are dependent on stocks' 52-week high prices. Section 3.1 shows that lottery-related anomalies have significantly negative profits in our sample by providing evidence of the MAX effect. Section 3.2 provides the results of the double-sort analysis based on NH and each of our lottery measures, MAX, LIDX, JPP, and ESKEW. Section 3.3 represents the supporting evidence of the double-sort analysis in subsamples based on institutional ownership. Finally, Section 3.4 reports the Fama and MacBeth (1973) regression results.

3.1 MAX Effect

First, we show that the MAX effect by Bali et al. (2011) is significant and negative in our sample. Table 1 represents average monthly raw returns and 4-factor alphas of decile portfolios sorted by MAX. We use monthly Fama-French three factors and the Carhart (1997) momentum factor when we calculate 4-factor alphas. Our adjusted t-statistics using the Newey-West (1987) method are reported in parentheses. We report both equal-weighted and value-weighted returns and the difference in the returns between the top and bottom decile portfolios. Consistent with Bali et al. (2011), we find that the MAX effect is significant and negative. Specifically, the average monthly equal-weighted raw returns and 4-factor alphas for MAX long-short portfolios are −0.92% with t-statistic −3.79 and −1.16% with t-statistic −8.01, respectively. For value-weighted returns, we find similar results.

[Table 1 about here]

Next, in Table 2, we provide summary statistics of each MAX decile portfolio and time-series average of cross-sectional correlations between our main variables. We find that the correlations of our lottery measures (MAX, LIDX, JPP, and ESKEW), the correlation between MAX and IVOL, and the correlations of NH, CGO, and MOM are positively high. Additionally, the correlation between NH and LOGME is positive, which implies stocks far from the 52-week high have greater limits to arbitrage since their size is small and their price is low. Moreover, the correlation between MAX and NH is negative. This implies that high MAX stocks are likely to be far from 52-week highs while low MAX stocks are likely to be near 52-week highs.

[Table 2 about here]

3.2 Interaction Between the 52-Week High and Lottery Measures

In this subsection, we examine the interaction between the 52-week high and our lottery measures. Our explanation is that the 52-week high serves as a psychological barrier, and investors consider it an upper bound for prices, which is consistent with Birru (2015). If stock prices are near 52-week highs, investors expect that these stock prices would not exceed their 52-week highs. Thus, investors do not overweight the right tail probability of the stock, since they expect that there is no right tail above its 52-week high. Therefore, investors hesitate to buy lottery stocks near the 52-week highs, and they no longer prefer these stocks. This leads to the absence of lottery-related anomalies among stocks near 52-week highs. On the other hand, for a stock far from its 52-week high, investors anchor on the 52-week high and consider that there is much room for the price to run up. Thus, they overestimate the probability of extreme positive returns and prefer stocks with lottery features among stocks far from 52-week highs. Therefore, lottery-related anomalies are strong among those stocks.

To test our explanation, we double-sort stocks into portfolios based on NH and MAX. Table 3 shows the returns for 25 double-sorted portfolios that are independently sorted into quintiles by NH and MAX. We report equal-weighted returns in Panel A and value-weighted returns in Panel B. We also show the difference in the returns between the top and bottom MAX quintile portfolios within each NH quintile portfolio. We find that the MAX effect is negative and strongly significant among stocks far from 52-week highs. However, this effect vanishes among stocks near 52-week highs. The difference in the MAX effect between the top and bottom NH quintiles is 2.17% with t-statistic 12.36, which is strongly positive and both statistically and economically significant. For 4-factor alphas and value-weighted returns, we find similar results.

[Table 3 about here]

We repeat our main empirical analysis using other lottery definitions rather than MAX. We use LIDX, JPP, and ESKEW as we explain in Section 2. We find similar results for all alternative lottery measures in the double-sort analysis. Table 4 shows the average monthly profits of lottery-related anomalies within each NH portfolio. Panel A reports the results for equal-weighted returns. As with the previous results for the MAX effect, the negative profits of the lottery-related anomalies significantly decrease as NH increase. Specifically, the differences in profits of lottery-related anomalies between the top and bottom NH quintiles are in the range of 0.74% to 1.49%. The t-statistics are in the range of 2.41 to 7.48. We find similar results for 4-factor alphas and value-weighted returns. We report the results of the value-weighted returns in Panel B.

[Table 4 about here]

3.3 The 52-Week High, Lottery Measures, and Institutional Ownership

We find that the interaction between lottery measures and NH is stronger among stocks with lower institutional ownership (IO) than stocks with high IO. Many papers support the theory that individual investors are more prone to behavioral biases rather than institutional investors (Odean, 1998; Barber and Odean, 2000, 2008; and Kumar, 2009). Thus, individual investors, rather than institutional investors, are more likely to consider a 52-week high a psychological barrier. Therefore, the dependency between lottery-related anomalies and NH would be pronounced among low IO stocks.

To test this, we conduct double-sort analyses in subsamples based on IO. Panel A of Table 5 shows the results. We consider two subsamples based on high IO (top 25%) and low IO (bottom 25%) groups. For each subsample, we independently double-sort stocks by NH and each of our lottery proxies. Then, we calculate the difference in profits of lottery-related anomalies between the high IO subsample and the low IO subsample. For our lottery measures, MAX, LIDX, JPP, and ESKEW, the differences are significantly negative. Specifically, the differences are in the range of −0.91% to −1.08% with t-statistics in the range of −2.25 to −3.24.

IO might be a proxy for limits to arbitrage since high IO stocks have fewer limits to arbitrage than low IO stocks. Thus, we replace IO with residual IO and repeat the analyses. We cross-sectionally regress IO on the natural logarithm of SIZE to obtain residual IO. We find similar results as when we analyze with IO. Panel B of Table 5 reports the results.[12] This result indicates that stocks with low IO are primarily affected by 52-week highs as psychological barriers.

[Table 5 about here]

3.4 The Fama and MacBeth Regression

Fama and MacBeth (1973) regression results also indicate that the anomalies induced by lottery preference are primarily small when stocks are near 52-week highs. Table 6 shows our main Fama and MacBeth (1973) regression results using the following equation.

$$\begin{aligned} R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}LOTT_{i,t} + \lambda_{2,t}NH_{i,t} + \lambda_{3,t}LOTT_{i,t} \cdot NH_{i,t} + \lambda_{4,t}BETA_{i,t} \\ +\lambda_{5,t}LOGME_{i,t} + \lambda_{6,t}LOGBM_{i,t} + \lambda_{7,t}MOM_{i,t} + \lambda_{8,t}SREV_{i,t} + \lambda_{9,t}ILLIQ_{i,t} \\ +\epsilon_{i,t+1} \end{aligned} \tag{3}$$

where LOGME and LOGBM are the natural logarithm of SIZE and BM, respectively. We consider each of our lottery measures MAX, LIDX, JPP, and ESKEW as LOTT. We represent the results as specifications (1) to (4) for each measure. The definitions of other variables are provided in the Appendix. All variables are standardized and winsorized.

Table 6 represents monthly Fama and MacBeth (1973) regressions results. Our interest is the coefficient for the interaction term between LOTT and NH, $\lambda_{3,t}$. For MAX as LOTT, this coefficient is 0.363 with t-statistic 11.02, which is strongly positive and both statistically and economically significant. This regression result indicates that for stocks near 52-week highs, the MAX effect is smaller compared to stocks far from 52-week highs. Specifically, if NH of stocks increases 1 sigma from their mean, the coefficient of MAX will become 0.176, which is positive. Meanwhile, if NH of

[12] We find relatively weak results for the difference in 4-factor alphas when we consider ESKEW as the lottery proxy. This is because the unconditional 4-factor alphas for long-short portfolios sorted by ESKEW are not significant in our sample.

stocks decreases 1 sigma from their mean, the coefficient of MAX will become −0.550, which is strongly negative. We find similar results for other lottery definitions, LIDX, JPP, and ESKEW as LOTT. The coefficients for the interaction terms are in the range of 0.094 to 0.237 with t-statistics in the range of 2.43 to 9.04. The results are all positively significant.

[Table 6 about here]

4. Alternative Explanations and Robustness Tests

In Sections 4.1 to 4.5, we discuss five different alternative explanations that might explain our empirical results. Then, we provide the evidence that show that these alternative explanations do not drive our results. Next, Section 4.6 provides the results of the robustness tests.

4.1 The Effect of Limits to Arbitrage

First, anomalies, including those that are lottery-related, are pronounced among stocks with greater arbitrage risk since there is greater mispricing of these stocks. Many studies document limits to arbitrage and mispricing (De Long et al., 1990; Shleifer and Vishny, 1997; and Mitchell et al., 2002). Moreover, Ali et al. (2003) and Mendenhall (2004) document that anomalies are pronounced among stocks with high arbitrage risk. Stocks far from the 52-week high tend to have greater limits to arbitrage since their size is small and their price is low. Thus, it might be possible that if stocks are far from the 52-week high, the MAX effect is pronounced because they have greater limits to arbitrage, not because of the NH effect.

To examine this concern, we consider size and price as proxies for arbitrage risk. Then, through triple-sort analysis, we show that our explanation is more supportive than this explanation. Table 7 shows the results. Stocks are first sorted by SIZE and grouped into three categories (top 30%, next 40%, and bottom 30%). Then, within each SIZE group, they are independently double-sorted by NH and MAX. The absolute magnitude of the MAX effect significantly decreases as NH increases for all SIZE groups. Specifically, the differences in the MAX effect between the top and bottom NH quintiles are in the range of 1.64% to 2.38%. The t-statistics are in the range of 6.93 to 9.80. However, when we sort stocks first by NH and double-sort by SIZE and MAX, the differences in the MAX effect are not significant. In other words, if we control for NH, the interaction between MAX and SIZE is not significant. We replace SIZE with PRC and find similar results.[13]

[Table 7 about here]

Additionally, by running Fama and MacBeth (1973) regressions, we show that the interaction between MAX and NH is significant even after controlling for the interaction between MAX and LOGME and between MAX and PRC. Table 8 shows the Fama and MacBeth (1973) regression results. The independent variables of specification (1) of this table are the same as specification (1) of Table 6. Specification (2) of Table 8 represents the regression result, which includes the interaction terms between MAX and LOGME and between MAX and PRC as independent variables. We find that the coefficient of the interaction term between MAX and NH is positively significant while the coefficients of the interaction terms between MAX and LOGME and between MAX and PRC are not significant. Specifically, the coefficient of the interaction term between MAX and NH is 0.354 with t-statistic 9.98. To summarize, our results of triple-sort analysis and Fama and MacBeth (1973) regressions in this subsection support that limits to arbitrage do not explain our results.

[Table 8 about here]

4.2 The Effect of Reference-Dependent Preferences

Second, An et al. (2017) document that lottery-related anomalies are dependent on capital gains overhang (CGO) by Grinblatt and Han (2005). The authors' explanation is that investors have reference-dependent preferences; investors prefer lottery stocks when they have lost money compared to when they have gained profits. This is consistent with the prospect theory of Kahneman and Tversky (1979)

[13] In this case, the interactions between MAX and PRC are only insignificant for the medium NH sample. However, even in the far and near NH samples, the magnitude and significance of the interactions between MAX and PRC are smaller and weaker than those of the interactions between MAX and NH in subsamples based on PRC.

and the mental accounting by Thaler (1980, 1985). The prospect theory implies that individuals have an S-shaped utility function, which leads to risk preference or lottery preference behavior of individuals when they are in the loss region. Moreover, by mental accounting, investors consider a different reference point for each asset, which indicates that a reference point for each stock is important. The effect of CGO might drive our results since our NH measure is correlated with CGO. It might be possible that when stocks near the 52-week high, investors do not prefer lottery stocks because they have gained profits, not because they have a psychological barrier.

To address the theory that our NH explanation is more promising than this explanation, we conduct triple-sort analyses. Table 7 shows the results. We sort stocks first by CGO and independently double-sort by NH and MAX. The absolute magnitude of the MAX effect significantly decreases as NH increases. Specifically, the differences in 4-factor alphas for the MAX long-short portfolio between the top and bottom NH quintiles are in the range of 1.08% to 1.35%. The t-statistics are in the range of 4.25 to 8.42. However, when we sort stocks first by NH and double-sort by CGO and MAX, this pattern is weak. If we control for NH, the interaction between MAX and CGO is weakly significant and is not significant when NH is high.

Moreover, by running Fama and MacBeth (1973) regressions, we show that the interaction between NH and MAX is both statistically and economically significant even after controlling for the interaction between NH and IVOL. Specification (3) of Table 8 shows the regression result, which includes the interaction term between MAX and CGO. We find that the coefficient of the interaction term between MAX and NH is positively significant while the coefficient of the interaction term between MAX and CGO is not significant. Specifically, the coefficient of the interaction term between MAX and NH is 0.320 with t-statistic 6.08. To summarize, our results suggest that the effect of CGO does not drive our results and that the effect of the 52-week high drives the CGO effect.

4.3 The Effect of Underreaction to New Information

The third possible alternative explanation is underreaction to new information (Zhang, 2006).

Zhang (2006) argues that price continuation is due to behavioral biases, and this drift should be greater for stocks with greater information uncertainty. Since high MAX stocks tend to have greater uncertainty, high MAX stocks exhibit high returns among stocks with good news while they exhibit low returns among stocks with bad news. This leads to weaker MAX effect among good news stocks than bad news stocks. We can use MOM by Jegadeesh and Titman (1993) as a proxy for new information, and it is correlated with our NH measure. Therefore, our results for the significant interaction between MAX and NH might be from this underreaction effect.

As in previous subsections, we verify that NH has a significant effect even after controlling for MOM while MOM does not have a significant effect after controlling for NH. Table 7 shows the results. When we sort stocks first by MOM and independently double-sort by NH and MAX, the absolute magnitude of the MAX effect significantly decreases as NH increases. Specifically, the differences in 4-factor alphas for the MAX long-short portfolios between the top and bottom NH quintiles are in the range of 0.90% to 1.86%. The t-statistics are in the range of 5.11 to 7.50. However, when we control for NH, the interaction between MAX and MOM is no longer significant. Specifically, the differences in the 4-factor alphas for the MAX long-short portfolios between the top and bottom MOM quintiles are in the range of 0.03% to 0.24%. The t-statistics are in the range of 0.13 to 1.13.

We additionally show that the interaction between MAX and NH is significant even after controlling for the interaction between MAX and MOM by running Fama and MacBeth (1973) regressions. Specification (4) of Table 8 represents the regression result. We include the interaction term between MAX and MOM as an independent variable. We find that the coefficient of the interaction term between MAX and NH is positively significant while the coefficient of the interaction term between MAX and MOM is negatively significant. Specifically, the coefficient of the interaction term between MAX and NH is 0.422 with t-statistic 11.23. To conclude, our results in this subsection indicate that the underreaction effect does not explain our results while our NH explanation explains the effect of underreaction on the MAX effect.

4.4 The Effect of Idiosyncratic Volatility

Fourth, Mbanga (2015) asserts that investors underreact to bad news particularly when stocks are far from 52-week highs, and idiosyncratic volatility (IVOL) can be a proxy for bad news. Thus, the IVOL effect documented by Ang et al. (2006) is stronger among stocks far from the 52-week high. Since IVOL and MAX are highly correlated, the IVOL effect might drive our result whereby the MAX effect is stronger among those stocks.

We conduct a double-sort analysis based on NH and residual MAX. We cross-sectionally regress MAX on IVOL to obtain residual MAX. We independently double-sort stocks into 25 portfolios based on NH and residual MAX. Panel A of Table 9 shows the results. As with the previous results, the residual MAX effect is negative and strongly significant among stocks far from 52-week highs, but this effect vanishes among stocks near 52-week highs. The difference in the residual MAX effect between the top and bottom NH quintiles is 1.28% with t-statistic 6.79, which is strongly positive and both statistically and economically significant.

Conversely, we cross-sectionally regress IVOL on MAX to obtain residual IVOL and conduct a double-sort analysis based on NH and residual IVOL. Panel B of Table 9 shows the results. In this case, we find that the interaction between NH and residual IVOL is reversed, which contradicts the prediction from the fourth alternative explanation. Specifically, the difference in the residual IVOL effect between the top and bottom NH quintiles is −0.68% with t-statistic −3.53. These results indicate that the MAX effect interacts with NH even after controlling for the IVOL effect. On the other hand, the IVOL effect does not interact or reversely interacts with NH when we control for the MAX effect.

[Table 9 about here]

Additionally, by running Fama and MacBeth (1973) regressions, we show that the interaction between NH and MAX is both statistically and economically significant even after controlling for the interaction between NH and IVOL. Specification (5) of Table 8 represents the regression result, which includes the interaction term between NH and IVOL as an independent variable. We find that the coefficient of the interaction term between MAX and NH is positively significant while the coefficient of the interaction term between IVOL and NH is not significant. Specifically, the coefficient of the interaction term between MAX and NH is 0.297 with t-statistic 7.56. In summary, our results in this subsection indicate that our NH explanation dominates the IVOL explanation.

Moreover, we run the Fama and MacBeth (1973) regression with independent variables including all five interaction terms discussed as alternative explanations. Specification (6) of Table 8 reports the regression result. We find that the interaction between NH and MAX is both statistically and economically significant even after controlling for other possible interaction effects including MAX-LOGME, MAX-PRC, MAX-CGO, MAX-MOM, and IVOL-NH. We again confirm our explanation based on the 52-week high that other alternative explanations do not drive our results.

4.5 The Effect of Liquidity Provision

Finally, we consider the effect of liquidity provision. It is possible that a high MAX stock near its 52-week high has greater selling pressure from liquidity providers, and the reversal would be smaller. Many papers document the role of liquidity provision on short-term reversals (Nagel, 2012; Kaniel et al., 2008; and Hameed and Mian, 2015). Cheng et al. (2016) show that past winner stocks have more liquidity providers so that monthly reversals are smaller among these stocks than past loser stocks. Moreover, past winner stocks are more likely to be liquid so the reversal would be smaller. Since stocks near their 52-week highs tend to be past winner stocks, our results might be driven by the liquidity provision effect.

Since the effect of liquidity is concentrated at the beginning of the month, we exclude the first five days of the month to remove this effect. Our methodology is the same as the methodology in Hur and Singh (2017). Table 10 shows the results. We find similar results with previous double-sort results in Table 3. Specifically, the difference in the MAX effect between the top and bottom NH quintiles is 1.53% with t-statistic 11.91, which is strongly positive and both statistically and economically significant. For the 4-factor alphas and value-weighted returns, we find similar results. This indicates that the liquidity effect does not drive our results.

[Table 10 about here]

4.6 Robustness Tests

Our empirical results are robust to various sample selections, alternative NH measures, and the consideration of other stock characteristics. Table 11 reports the results of robustness tests. We represent the average of monthly MAX strategy profits within each NH portfolio for our subsamples. In Panel A, we divide our full sample period into three subperiods. The first period is from July 1963 to December 1979, the second period is from January 1980 to December 1999, and the third period is from January 2000 to December 2016. We find similar results for all subperiod samples. We also find similar results when excluding NASDAQ samples. Next, we consider alternative NH measures in addition to nearness to the 52-week high price. We use nearness to the 13, 26, and 104-week high price as alternative NH measures. The results are shown in Panel B and are similar to previous results.

Moreover, similar results are observed when we control for other stock characteristics such as illiquidity, size, and stock price. Panel C of Table 11 shows the results. Stocks are first sorted by illiquidity, size, and stock price and grouped into three categories (top 30%, next 40%, and bottom 30%). Then, within each group, the stocks are independently double-sorted into 25 portfolios based on NH and MAX. The absolute magnitude of the MAX effect significantly decreases as NH increases for all subsamples by stock characteristics. Specifically, the differences in the 4-factor alphas for the MAX long-short portfolios between the top and bottom NH quintiles are in the range of 1.25% to 2.22%. The t-statistics are in the range of 6.69 to 9.31. These results show that our results are not driven just by illiquid stocks, small stocks, or low-priced stocks. Our results are also robust for liquid stocks, large stocks, and high-priced stocks.

[Table 11 about here]

5. Conclusion

We show that lottery-related anomalies are primarily strong among stocks far from 52-week highs. The results suggest that the 52-week high price affects the lottery preferences of investors. Therefore, anomalies induced by lottery preference depend on nearness to the 52-week high. This is because the 52-week high serves as a psychological barrier, and investors consider it an upper bound for prices. Thus, investors no longer prefer lottery stocks if these stocks are near their 52-week highs. We find that this dependency is pronounced among stocks with low institutional ownership. This is because individual investors are more affected by 52-week highs than institutional investors.

Moreover, we consider various alternative explanations that might explain our main results. They are effects of limits to arbitrage, reference-dependent preference, underreaction to new information, idiosyncratic volatility, and liquidity provision. Then, we provide evidence that these alternative explanations do not drive our results. Our empirical results are robust to various sample selections, alternative definitions of NH measures, and the consideration of other stock characteristics.

Our paper contributes to the literature in several ways. First, we find that lottery preferences of investors depend on 52-week highs that can serve as psychological barriers or anchors. Thus, the magnitude of lottery-related anomalies varies with nearness to 52-week highs. To our knowledge, this is the first study to connect psychological barriers and lottery preference. Second, this paper explains the 52-week high effect on investor behavior by the belief-based explanation. The 52-week high price can serve as a psychological barrier so that investors do not believe right tail probability or extreme positive returns of stocks near 52-week highs. This belief-based explanation is consistent with Birru (2015).

Appendix. Variable Descriptions

MAX: MAX is the maximum daily return within a month as in Bali et al. (2011). MAX of stock i at the end of the month t is the same as Equation (1).

NH: NH is a ratio of the current price to the 52-week high price. NH of stock i at the end of the month t is the same as Equation (2).

CGO: We follow Grinblatt and Han (2005) to compute capital gains overhang (CGO), but we use daily data. The reference price for each stock i is estimated as follows:

$$RP_{i,t} = \frac{1}{k}\sum_{n=1}^{T}\left(V_{i,t-n}\prod_{\tau=1}^{n-1}\left[1 - V_{i,t-n+\tau}\right]\right)P_{t-n}, \tag{4}$$

where $V_{i,t}$ is the turnover in stock i on day t, $P_{i,t}$ is the price of stock i at the end of day t, T is the number of trading days in the previous 3 years, and k is a constant that makes the weights on P_{t-n} have summation 1. CGO of stock i at the end of the month t is obtained by

$$CGO_{i,t} = \frac{P_{i,t-1} - RP_{i,t}}{P_{i,t-1}}, \tag{5}$$

where $P_{i,t}$ is the price of stock i at the end of month t, and we use the reference price on the last trading day of month t.

IVOL: IVOL is the idiosyncratic volatility, over the previous month. We use the single factor model to estimate the idiosyncratic return on day d using daily returns within each month for each stock.

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_i\left(R_{m,d} - R_{f,d}\right) + \epsilon_{i,d}, \tag{6}$$

where $R_{i,d}$ is the return on stock i on day d, $R_{m,d}$ is the market return on day d, and $R_{f,d}$ is the T-Bill return on day d. IVOL of stock i at the end of the month t is defined as the standard deviation of daily residuals, $\epsilon_{i,d}$, in month t.

BETA: BETA is the market beta over the previous month. We consider nonsynchronous trading and use the current, lag, and lead market return when estimating beta. We estimate beta using daily returns within each month for each stock.

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_{1,i}(R_{m,d-1} - R_{f,d-1}) + \beta_{2,i}(R_{m,d} - R_{f,d}) + \beta_{3,i}(R_{m,d+1} - R_{f,d+1}) + \epsilon_{i,d}, \tag{7}$$

where $R_{i,d}$ is the return on stock i on day d, $R_{m,d}$ is the market return on day d, and $R_{f,d}$ is the T-Bill return on day d. BETA of stock i at the end of the month t is calculated by $\widehat{\beta_{1,i}} + \widehat{\beta_{2,i}} + \widehat{\beta_{3,i}}$.

SIZE: SIZE is the market value of equity in millions of dollars at the end of month t for each stock.

BM: BM is the book-to-market ratio in month t. Following Fama and French (1992), we use the market value of equity at the end of December of the previous year and book value at the end of the previous fiscal year.

LOGME: LOGME is the natural logarithm of SIZE.

LOGBM: LOGBM is the natural logarithm of BM.

MOM: Following Jegadeesh and Titman (1993), MOM is the previous 11-month returns with a one-month lag for each stock.

SREV: Following Jegadeesh (1990), SREV is the previous month's return.

ILLIQ: ILLIQ is the illiquidity measure as in Amihud (2002).

PRC: PRC is the natural logarithm of the stock price at the end of month t for each stock.

LIDX: Lottery stock index as in Han and Kumar (2013). For details, see the definition of LOTT in the description of Table 1 on page 383 in Han and Kumar (2013).

JPP: Jackpot probability as in Conrad et al. (2014). For details, see Equation (1) on page 460 in Conrad et al. (2014).

ESKEW: Expected idiosyncratic skewness as in Boyer et al. (2010). For details, see Equation (1) and (2) on page 174, Equation (3) on page 175, and Equation (4) on page 176 in Boyer et al. (2010).

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Table 1. MAX Portfolio Returns

Table 1 represents the average of monthly raw returns and 4-factor alphas for each MAX decile portfolio. We sort stocks into decile portfolios based on the maximum daily returns over the previous month (MAX) following Bali et al. (2011). We report both equal-weighted and value-weighted returns and the difference in the returns between the top and bottom decile portfolios. We use monthly Fama-French three factors and the Carhart (1997) momentum factor when we calculate 4-factor alphas. Our adjusted t-statistics using the Newey-West (1987) method are reported in parentheses. The sample period is from July 1963 to December 2016.

	Equal-Weighted Returns		Value-Weighted Returns	
MAX decile	Raw return	4-factor alpha	Raw return	4-factor alpha
1 (Low)	1.14	0.25	0.97	0.13
2	1.31	0.32	0.94	0.04
3	1.38	0.34	0.96	0.05
4	1.37	0.30	0.87	−0.03
5	1.36	0.26	1.01	0.06
6	1.26	0.12	1.02	0.07
7	1.16	0.00	0.95	−0.07
8	1.01	−0.13	0.86	−0.15
9	0.77	−0.37	0.81	−0.25
10 (High)	0.21	−0.90	0.31	−0.70
10−1	−0.92	−1.16	−0.66	−0.83
	(−3.79)	(−8.01)	(−2.25)	(−4.21)

Table 2. Summary Statistics

Panel A of Table 2 represents summary statistics for each MAX decile portfolio. We sort stocks into decile portfolios based on the maximum daily returns over the previous month (MAX). We report for each decile portfolio the monthly average of MAX, the nearness to 52-week highs (NH), lottery stock index (LIDX), jackpot probability (JPP), expected idiosyncratic skewness (ESKEW), capital gains overhang (CGO), idiosyncratic volatility (IVOL), market beta (BETA), the market value of equity in millions of dollars (SIZE), book-to-market ratio (BM), and the previous 11-month returns with a one-month lag (MOM). Panel B represents the time-series average of cross-sectional correlations between MAX, NH, LIDX, JPP, ESKEW, LOGME, CGO, MOM, and IVOL. The details of variable definitions are shown in the Appendix. The sample period is from July 1963 to December 2016, except for JPP (July 1972 to December 2016) and ESKEW (January 1988 to December 2016).

Panel A: Summary Statistics

MAX Decile	MAX	NH	LIDX	JPP	ESKEW	CGO	IVOL	BETA	SIZE	BM	MOM
1 (Low)	1.31	0.864	0.311	0.69	0.918	0.029	0.86	0.29	3734.1	0.859	16.82
2	2.30	0.849	0.324	0.64	0.897	0.024	1.21	0.49	3485.9	0.812	15.71
3	2.95	0.838	0.352	0.69	0.918	0.019	1.44	0.65	2867.8	0.793	16.18
4	3.57	0.827	0.382	0.75	0.940	0.012	1.66	0.74	2267.7	0.786	17.16
5	4.23	0.815	0.415	0.84	0.959	0.003	1.89	0.84	1833.1	0.782	18.54
6	4.99	0.803	0.450	0.93	0.977	−0.008	2.14	0.94	1474.4	0.787	20.02
7	5.91	0.790	0.489	1.02	1.000	−0.022	2.43	1.04	1171.9	0.787	22.13
8	7.14	0.776	0.532	1.14	1.027	−0.040	2.80	1.15	911.8	0.789	24.37
9	9.09	0.760	0.587	1.32	1.059	−0.068	3.33	1.27	684.7	0.798	26.80
10 (High)	15.98	0.749	0.690	1.75	1.125	−0.117	4.91	1.52	486.3	0.837	28.15

Panel B: Correlations

	MAX	NH	LIDX	JPP	ESKEW	LOGME	CGO	MOM	IVOL
MAX	1	−0.1658	0.5784	0.4116	0.1362	−0.2102	−0.1236	0.0156	0.8764
NH		1	−0.2648	−0.2908	−0.1676	0.2050	0.6483	0.3761	−0.3274
LIDX			1	0.5842	0.3463	−0.5492	−0.1966	0.0337	0.6547
JPP				1	0.4571	−0.7088	−0.2314	−0.0069	0.5061
ESKEW					1	−0.5697	−0.1756	−0.1783	0.1889
LOGME						1	0.1780	0.0251	−0.3009
CGO							1	0.5309	−0.2007
MOM								1	0.0278
IVOL									1

Table 3. Double-sort Analysis

Table 3 represents the average of monthly raw returns for each double-sorted portfolio. We independently double-sort stocks into 25 portfolios based on the nearness to 52-week high (NH) and the maximum daily returns over the previous month (MAX). We report equal-weighted returns in Panel A and value-weighted returns in Panel B. We also represent the difference in the raw returns and 4-factor alphas between the top and bottom MAX quintile portfolios within each NH quintile portfolio. Additionally, we report the difference in the MAX effect between the top and bottom NH quintiles. We use monthly Fama-French three factors and the Carhart (1997) momentum factor when we calculate 4-factor alphas. Our adjusted t-statistics using the Newey-West (1987) method are reported in parentheses. The sample period is from July 1963 to December 2016.

Panel A: Equal-Weighted Returns

		MAX						
		1 (Low)	2	3	4	5 (High)	5−1	4-factor alpha
	1 (Far)	1.51	1.60	1.27	0.73	−0.35	−1.86	−1.97
							(−10.36)	(−14.89)
	2	1.41	1.52	1.30	0.98	0.30	−1.11	−1.43
							(−5.34)	(−9.77)
NH	3	1.29	1.39	1.38	1.18	0.88	−0.40	−0.78
							(−1.82)	(−5.69)
	4	1.20	1.28	1.36	1.38	1.25	0.04	−0.34
							(0.21)	(−2.43)
	5 (Near)	1.08	1.19	1.31	1.33	1.39	0.30	−0.06
							(1.70)	(−0.49)
	5−1						2.17	1.91
							(12.36)	(11.50)

Panel B: Value-Weighted Returns

		MAX						
		1 (Low)	2	3	4	5 (High)	5−1	4-factor alpha
	1 (Far)	1.64	1.10	0.90	0.48	−0.41	−2.06	−2.28
							(−8.12)	(−10.61)
	2	1.35	1.04	0.97	0.68	0.36	−0.98	−1.36
							(−3.97)	(−6.96)
NH	3	1.11	0.90	0.98	0.84	0.86	−0.25	−0.63
							(−0.95)	(−3.52)
	4	0.94	0.91	1.07	1.07	1.30	0.36	0.00
							(1.46)	(0.04)
	5 (Near)	0.74	0.87	0.92	1.15	1.25	0.51	0.28
							(2.42)	(1.68)
	5−1						2.57	2.56
							(8.67)	(8.76)

Table 4. Double-Sort Analysis for Other Lottery Feature Definitions

Table 4 represents the average of monthly profits of lottery-related anomalies within each NH portfolio. We independently double-sort stocks into 25 portfolios based on NH and LOTT. We consider LOTT as MAX, LIDX, JPP, or ESKEW. The details of variable definitions are shown in the Appendix. We also represent the difference in the profits of lottery-related anomalies between the top and bottom NH quintile portfolios. We report equal-weighted returns in Panel A and value-weighted returns in Panel B. We use monthly Fama-French three factors and the Carhart (1997) momentum factor when we calculate 4-factor alphas. Our adjusted t-statistics using the Newey-West (1987) method are reported in parentheses. The sample period is from July 1963 to December 2016, except for JPP (July 1972 to December 2016) and ESKEW (January 1988 to December 2016).

Panel A: Equal-Weighted Returns

	NH						
LOTT	1 (Far)	2	3	4	5 (Near)	5−1	4-factor alpha
MAX	−1.86	−1.11	−0.40	0.04	0.30	2.17	1.91
	(−10.36)	(−5.34)	(−1.82)	(0.21)	(1.70)	(12.36)	(11.50)
LIDX	−0.92	−0.40	0.08	0.33	0.58	1.49	1.44
	(−4.22)	(−2.35)	(0.41)	(1.64)	(3.55)	(7.48)	(7.74)
JPP	−0.45	−0.43	0.15	0.57	0.70	1.15	1.29
	(−2.19)	(−2.11)	(0.76)	(2.51)	(3.66)	(4.71)	(5.30)
ESKEW	−0.48	−0.15	−0.21	−0.01	0.26	0.74	0.83
	(−2.03)	(−1.02)	(−1.11)	(−0.10)	(1.24)	(2.41)	(2.88)

Panel B: Value-Weighted Returns

	NH						
LOTT	1 (Far)	2	3	4	5 (Near)	5−1	4-factor alpha
MAX	−2.06	−0.98	−0.25	0.36	0.51	2.57	2.56
	(−8.12)	(−3.97)	(−0.95)	(1.46)	(2.42)	(8.67)	(8.76)
LIDX	−1.15	−0.65	0.04	0.31	0.47	1.62	1.93
	(−4.52)	(−3.21)	(0.18)	(1.44)	(2.47)	(5.34)	(6.31)
JPP	−0.64	−0.40	0.27	0.56	0.67	1.32	1.46
	(−2.47)	(−1.56)	(1.07)	(2.10)	(2.61)	(4.33)	(4.70)
ESKEW	−0.34	0.05	−0.11	0.21	0.07	0.41	0.54
	(−1.22)	(0.16)	(−0.44)	(0.80)	(0.23)	(1.14)	(1.50)

Table 5. Double-Sort Analysis in Subsamples Based on Institutional Ownership

Table 5 represents the average of monthly profits of lottery-related anomalies within each NH portfolio. In Panel A, stocks are first sorted by institutional ownership (IO). Then, within high (top 25%) and low (bottom 25%) IO groups, they are independently double-sorted by NH and LOTT. We report the difference between top and bottom LOTT quintile returns within each IO-NH portfolio. We also represent the difference in the LOTT strategy profits between the top and bottom NH quintile portfolios within each IO group. In Panel B, we replace IO with residual IO and do the same. We cross-sectionally regress IO on LOGME to obtain residual IO. We consider LOTT as MAX, LIDX, JPP, or ESKEW. The details of variable definitions are given in the Appendix. We use monthly Fama-French three factors and the Carhart (1997) momentum factor when we calculate 4-factor alphas. Our adjusted t-statistics using the Newey-West (1987) method are reported in parentheses. The sample period is from July 1963 to December 2016, except for JPP (July 1972 to December 2016) and ESKEW (January 1988 to December 2016).

Panel A: Subsamples Based on IO

		NH						
LOTT		1 (Far)	2	3	4	5 (Near)	5−1	4-factor alpha
	Low IO	−2.46	−1.51	−0.71	−0.28	−0.22	2.24	2.03
		(−9.96)	(−5.82)	(−2.10)	(−0.85)	(−0.83)	(8.19)	(7.33)
MAX	High IO	−1.11	−0.72	−0.18	0.18	0.16	1.27	1.28
		(−4.48)	(−3.03)	(−0.72)	(0.68)	(0.69)	(5.38)	(5.89)
	High−Low						−0.97	−0.75
							(−3.24)	(−2.44)
	Low IO	−1.65	−1.29	−0.35	0.17	−0.01	1.63	1.54
		(−6.73)	(−4.59)	(−0.97)	(0.48)	(−0.04)	(5.81)	(5.57)
LIDX	High IO	−0.22	−0.10	0.30	0.32	0.43	0.65	0.81
		(−0.88)	(−0.60)	(1.57)	(1.57)	(2.61)	(2.71)	(3.75)
	High−Low						−0.97	−0.73
							(−3.24)	(−2.55)
	Low IO	−1.08	−0.76	−0.14	0.37	0.58	1.70	1.66
		(−3.24)	(−2.80)	(−0.44)	(1.02)	(2.00)	(4.26)	(4.20)
JPP	High IO	−0.27	−0.38	0.19	0.06	0.33	0.61	0.64
		(−0.96)	(−1.77)	(0.73)	(0.24)	(1.59)	(2.07)	(2.19)
	High−Low						−1.08	−1.02
							(−2.49)	(−2.32)
	Low IO	−0.31	0.02	−0.11	−0.20	0.10	0.42	0.29
		(−1.12)	(0.10)	(−0.55)	(−0.91)	(0.46)	(1.27)	(0.92)
ESKEW	High IO	0.20	−0.00	0.03	−0.36	−0.28	−0.48	−0.41
		(0.75)	(−0.00)	(0.15)	(−1.34)	(−1.16)	(−1.51)	(−1.24)
	High−Low						−0.91	−0.70
							(−2.25)	(−1.63)

Table 5. Double-sort Analysis in Subsamples Based on Institutional Ownership − Continued

Panel B: Subsamples Based on Residual IO

		NH						
LOTT		1 (Far)	2	3	4	5 (Near)	5−1	4-factor alpha
	Low IO	−2.40	−1.61	−0.66	−0.07	−0.14	2.26	2.20
		(−9.17)	(−4.90)	(−1.80)	(−0.20)	(−0.58)	(7.87)	(7.86)
MAX	High IO	−0.99	−0.97	−0.13	−0.06	0.27	1.27	1.14
		(−3.73)	(−4.61)	(−0.51)	(−0.28)	(1.04)	(4.69)	(4.60)
	High−Low						−0.99	−1.06
							(−3.74)	(−4.06)
	Low IO	−2.64	−1.24	−0.42	0.13	0.15	2.73	2.79
		(−6.60)	(−4.03)	(−1.19)	(0.36)	(0.56)	(6.49)	(6.73)
LIDX	High IO	−0.44	−0.25	0.15	0.38	0.59	1.03	1.20
		(−1.81)	(−1.33)	(0.79)	(2.03)	(3.64)	(3.79)	(4.54)
	High−Low						−1.70	−1.58
							(−4.29)	(−4.03)
	Low IO	−1.23	−0.64	0.15	0.08	0.75	2.01	2.31
		(−4.08)	(−2.02)	(0.40)	(0.21)	(2.18)	(5.21)	(6.31)
JPP	High IO	−0.08	−0.73	−0.11	0.04	0.39	0.48	0.37
		(−0.28)	(−3.65)	(−0.52)	(0.22)	(1.53)	(1.29)	(1.08)
	High−Low						−1.53	−1.94
							(−3.80)	(−4.96)
	Low IO	−0.59	−0.05	−0.10	0.09	0.27	0.87	0.68
		(−1.78)	(−0.20)	(−0.41)	(0.36)	(1.15)	(2.29)	(1.90)
ESKEW	High IO	0.29	0.17	−0.06	−0.20	−0.16	−0.45	−0.33
		(1.09)	(0.91)	(−0.27)	(−0.85)	(−0.56)	(−1.08)	(−0.80)
	High−Low						−1.32	−1.02
							(−2.80)	(−2.11)

Table 6. Fama and MacBeth (1973) Regressions

Table 6 represents the times-series averages of firm-level cross-sectional regressions coefficients. We run monthly Fama and MacBeth (1973) regressions of the stock return on the lagged independent variables. Our independent variables are LOTT, NH, the interaction term between LOTT and NH, BETA, LOGME, LOGBM, MOM, SREV, and ILLIQ. We consider LOTT as MAX, LIDX, JPP, or ESKEW. Details of variable definitions are in the Appendix. We use monthly Fama-French three factors and the Carhart (1997) momentum factor when we calculate 4-factor alphas. All variables are standardized and winsorized. Our adjusted t-statistics using the Newey-West (1987) method are reported in parentheses. The sample period is from July 1963 to December 2016, except for JPP (July 1972 to December 2016) and ESKEW (January 1988 to December 2016).

	(1) LOTT = MAX	(2) LOTT = LIDX	(3) LOTT = JPP	(4) LOTT = ESKEW
LOTT	−0.187	−0.058	−0.162	−0.033
	(−4.21)	(−1.29)	(−2.39)	(−0.67)
NH	0.157	0.205	0.173	0.238
	(2.39)	(3.15)	(2.36)	(2.15)
LOTT*NH	0.363	0.237	0.146	0.094
	(11.02)	(9.04)	(4.33)	(2.43)
BETA	0.113	0.060	0.002	−0.171
	(0.93)	(0.54)	(0.06)	(−1.24)
LOGME	−0.197	−0.200	−0.240	−0.115
	(−3.43)	(−3.72)	(−3.72)	(−1.81)
LOGBM	0.168	0.184	0.156	0.154
	(2.97)	(3.21)	(2.68)	(1.88)
MOM	0.326	0.299	0.289	0.276
	(4.18)	(3.82)	(3.31)	(2.15)
SREV	−0.556	−0.648	−0.558	−0.432
	(−11.18)	(−12.03)	(−9.42)	(−5.36)
ILLIQ	−0.259	−0.285	−0.487	−0.491
	(−3.70)	(−3.93)	(−2.02)	(−4.36)

Table 7. Triple-sort Analysis

Table 7 represents the average of monthly MAX strategy profits within each portfolio. In Panel A, stocks are first sorted by SIZE and grouped into three categories (top 30%, next 40%, and bottom 30%). Then, within each SIZE group, they are independently double-sorted by NH and MAX. We report the difference between top and bottom MAX quintile returns within each 15 SIZE -NH portfolio. We also represent the difference in the MAX strategy profits between the top and bottom NH quintile portfolios within each SIZE group. We replace SIZE with PRC, CGO, and MOM and do the same. In Panel B, stocks are first sorted by NH and within each NH group they are independently double-sorted by SIZE and MAX. We report differences between top and bottom MAX quintile returns within each 15 NH-SIZE portfolio. We also represent the difference in the MAX strategy profits between the top and bottom SIZE quintile portfolios within each NH group. We replace SIZE with PRC, CGO, and MOM and do the same. We use monthly Fama-French three factors and the Carhart (1997) momentum factor when we calculate 4-factor alphas. Our adjusted t-statistics using the Newey-West (1987) method are reported in parentheses. The sample period is from July 1963 to December 2016.

Panel A: MAX Strategy Profits Within Each SIZE-NH, PRC-NH, CGO-NH, and MOM-NH Portfolio

		NH						
		1 (Far)	2	3	4	5 (Near)	5−1	4-factor alpha
	1 (Low)	−1.95	−1.60	−0.94	−0.39	−0.31	1.64	1.50
		(−9.36)	(−7.36)	(−4.01)	(−1.61)	(−1.69)	(6.93)	(6.50)
SIZE	2 (Medium)	−2.11	−1.32	−0.75	−0.17	0.26	2.38	2.01
		(−9.48)	(−6.24)	(−3.24)	(−0.69)	(1.18)	(9.80)	(8.89)
	3 (High)	−1.43	−0.80	−0.02	0.19	0.25	1.70	1.56
		(−6.49)	(−3.85)	(−0.12)	(0.85)	(1.44)	(7.80)	(7.81)
	1 (Low)	−2.85	−2.16	−1.62	−1.00	−0.40	2.44	2.12
		(−12.29)	(−9.88)	(−7.36)	(−3.92)	(−1.77)	(9.22)	(8.42)
PRC	2 (Medium)	−1.85	−1.18	−0.47	−0.04	0.09	1.94	1.57
		(−9.52)	(−6.21)	(−2.29)	(−0.23)	(0.48)	(9.01)	(7.82)
	3 (High)	−1.11	−0.26	0.12	0.27	0.23	1.35	1.25
		(−4.92)	(−1.07)	(0.50)	(1.08)	(1.38)	(6.97)	(6.69)
	1 (Low)	−2.12	−2.03	−1.38	−1.26	−0.62	1.50	1.15
		(−8.17)	(−9.67)	(−5.77)	(−5.29)	(−2.49)	(5.35)	(4.25)
CGO	2 (Medium)	−1.22	−0.92	−0.24	−0.10	0.24	1.46	1.35
		(−5.85)	(−4.38)	(−1.30)	(−0.51)	(1.26)	(9.19)	(8.42)
	3 (High)	−0.66	0.08	0.39	0.33	0.47	1.13	1.08
		(−2.97)	(0.34)	(1.61)	(1.38)	(2.49)	(5.09)	(4.93)
	1 (Loser)	−2.66	−1.91	−1.66	−1.32	−0.63	2.02	1.86
		(−10.24)	(−8.73)	(−7.99)	(−5.95)	(−3.21)	(6.85)	(6.51)
MOM	2 (Medium)	−0.92	−0.47	−0.17	0.09	0.09	1.01	0.90
		(−4.54)	(−2.70)	(−0.94)	(0.51)	(0.65)	(5.63)	(5.11)
	3 (Winner)	−1.67	−0.51	0.01	0.30	0.40	2.08	1.86
		(−8.29)	(−2.05)	(0.07)	(1.21)	(1.88)	(8.22)	(7.50)

Table 7. Triple-sort Analysis − Continued

Panel B: MAX Strategy Profits Within Each NH-SIZE, NH-PRC, NH-CGO, and NH-MOM Portfolio

		SIZE						
		1 (Low)	2	3	4	5 (High)	5−1	4-factor alpha
	1 (Far)	−1.95	−2.38	−2.23	−2.14	−1.96	−0.03	0.04
		(−9.15)	(−10.09)	(−8.98)	(−8.50)	(−7.07)	(−0.16)	(0.19)
NH	2 (Medium)	−0.50	−0.48	−0.60	−0.70	−0.19	0.31	0.46
		(−2.25)	(−2.29)	(−2.57)	(−3.34)	(−0.78)	(1.26)	(2.03)
	3 (Near)	0.05	0.08	0.16	0.16	0.20	0.13	0.32
		(0.34)	(0.39)	(0.68)	(0.81)	(0.80)	(0.56)	(1.33)
		PRC						
		1 (Low)	2	3	4	5 (High)	5−1	4-factor alpha
	1 (Far)	−2.43	−2.23	−2.21	−2.05	−1.63	0.80	0.78
		(−10.51)	(−9.37)	(−8.35)	(−8.63)	(−5.99)	(2.99)	(2.89)
NH	2 (Medium)	−0.41	−0.59	−0.65	−0.42	−0.08	0.32	0.47
		(−1.71)	(−3.12)	(−3.36)	(−1.99)	(−0.31)	(1.27)	(2.03)
	3 (Near)	0.06	0.23	−0.02	0.24	0.60	0.53	0.70
		(0.31)	(1.13)	(−0.12)	(1.26)	(2.39)	(2.21)	(3.02)
		CGO						
		1 (Low)	2	3	4	5 (High)	5−1	4-factor alpha
	1 (Far)	−2.32	−2.07	−1.52	−1.69	−1.40	0.91	0.81
		(−8.56)	(−8.24)	(−6.43)	(−7.86)	(−6.27)	(3.03)	(2.71)
NH	2 (Medium)	−0.48	−0.74	−0.49	−0.45	0.01	0.50	0.50
		(−2.29)	(−3.97)	(−2.57)	(−2.02)	(0.06)	(2.45)	(2.47)
	3 (Near)	−0.09	0.40	0.22	0.16	0.41	0.50	0.40
		(−0.47)	(1.89)	(1.27)	(0.77)	(1.92)	(2.39)	(1.87)
		MOM						
		1 (Low)	2	3	4	5 (High)	5−1	4-factor alpha
	1 (Far)	−2.45	−1.84	−1.65	−1.59	−2.25	0.20	0.03
		(−9.71)	(−7.87)	(−6.91)	(−7.18)	(−11.41)	(0.81)	(0.13)
NH	2 (Medium)	−0.87	−0.27	−0.40	−0.26	−0.61	0.25	0.16
		(−4.87)	(−1.56)	(−2.11)	(−1.11)	(−2.52)	(1.35)	(0.87)
	3 (Near)	−0.04	0.34	0.04	0.04	0.48	0.53	0.24
		(−0.32)	(2.01)	(0.24)	(0.21)	(1.97)	(2.33)	(1.13)

Table 8. Fama and MacBeth (1973) Regressions Controlling for Other Interaction Effects

Table 8 represents the times-series averages of firm-level cross-sectional regressions coefficients. We run monthly Fama and MacBeth (1973) regressions of the stock return on the lagged independent variables. Our independent variables of specification (1) are the same as specification (1) of Table 6. The independent variables are MAX, NH, the interaction term between MAX and NH, BETA, LOGME, LOGBM, MOM, SREV, and ILLIQ. In specification (2), we include the interaction terms between MAX and LOGME, and between MAX and PRC. In specification (3), we include the interaction term between MAX and CGO. In specification (4), we include the interaction term between MAX and MOM. In specification (5), we include the interaction term between IVOL and NH. In specification (6), we include the five interactions terms in specification (2), (3), (4), and (5). The details of variable definitions are shown in the Appendix. All variables are standardized and winsorized. Our adjusted t-statistics using the Newey-West (1987) method are reported in parentheses. The sample period is from July 1963 to December 2016.

	(1)	(2)	(3)	(4)	(5)	(6)
MAX	−0.187	−0.194	−0.164	−0.196	0.117	0.132
	(−4.21)	(−4.36)	(−3.70)	(−4.42)	(1.76)	(2.10)
NH	0.157	0.183	0.016	0.144	0.094	−0.034
	(2.39)	(3.05)	(0.20)	(2.15)	(1.50)	(−0.45)
MAX*NH	0.363	0.354	0.320	0.422	0.297	0.323
	(11.02)	(9.98)	(6.08)	(11.23)	(7.56)	(6.03)
MAX*LOGME		0.060				−0.032
		(1.21)				(−0.60)
MAX*PRC		−0.005				0.015
		(−0.13)				(0.37)
MAX*CGO			0.060			0.142
			(1.27)			(2.29)
MAX*MOM				−0.150		−0.264
				(−4.01)		(−5.10)
IVOL*NH					0.079	0.045
					(1.45)	(0.70)
BETA	0.113	0.127	0.086	0.109	0.096	0.095
	(0.93)	(1.02)	(0.68)	(0.94)	(0.82)	(0.74)
LOGME	−0.197	−0.128	−0.194	−0.192	−0.227	−0.182
	(−3.43)	(−2.45)	(−3.30)	(−3.39)	(−4.09)	(−3.43)
LOGBM	0.168	0.152	0.161(	0.170	0.155	0.132
	(2.97)	(2.73)	3.00)	(3.02)	(2.77)	(2.49)
MOM	0.326	0.334	0.264	0.364	0.361	0.332
	(4.18)	(4.18)	(3.16)	(4.32)	(4.84)	(3.82)
SREV	−0.556	−0.555	−0.551	−0.557	−0.604	−0.590
	(−11.18)	(−10.99)	(−10.85)	(−11.07)	(−12.39)	(−11.47)
ILLIQ	−0.259	−0.239	−0.293	−0.263	−0.207	−0.255
	(−3.70)	(−3.67)	(−2.87)	(−3.76)	(−2.81)	(−2.44)
PRC		−0.111				−0.119
		(−2.21)				(−2.43)
CGO			0.116			0.132
			(2.15)			(2.40)
IVOL					−0.342	−0.377
					(−4.03)	(−4.45)

Table 9. Double-Sort Analysis for Residual MAX and Residual IVOL

Table 9 represents the average of monthly raw returns for each double-sorted portfolio. In Panel A, we independently double-sort stocks into 25 portfolios based on NH and residual MAX. We cross-sectionally regress MAX on IVOL to obtain residual MAX. We also represent the difference in the raw returns and 4-factor alphas between the top and bottom residual MAX quintile portfolios within each NH quintile portfolio. Additionally, we report the difference in the residual MAX effect between the top and bottom NH quintiles. In Panel B, we independently double-sort stocks into 25 portfolios based on NH and residual IVOL. We cross-sectionally regress IVOL on MAX to obtain residual IVOL. We also represent the difference in the raw returns and 4-factor alphas between the top and bottom residual IVOL quintile portfolios within each NH quintile portfolio. Additionally, we report the difference in the residual IVOL effect between the top and bottom NH quintiles. We use monthly Fama-French three factors and the Carhart (1997) momentum factor when we calculate 4-factor alphas. Our adjusted t-statistics using the Newey-West (1987) method are reported in parentheses. The sample period is from July 1963 to December 2016.

Panel A: Residual MAX

		Residual MAX						
		1 (Low)	2	3	4	5 (High)	5−1	4-factor alpha
	1 (Far)	0.91	0.88	0.80	0.46	−0.11	−1.03	−1.03
		(2.92)	(2.96)	(2.75)	(1.47)	(−0.35)	(−8.43)	(−8.63)
	2	1.16	1.26	1.19	1.01	0.62	−0.54	−0.52
		(4.52)	(5.23)	(5.02)	(4.11)	(2.12)	(−4.55)	(−4.74)
NH	3	1.34	1.37	1.29	1.14	1.03	−0.31	−0.22
		(5.10)	(6.16)	(6.23)	(5.23)	(4.04)	(−2.91)	(−2.19)
	4	1.36	1.39	1.32	1.22	1.25	−0.10	0.00
		(5.69)	(6.95)	(7.06)	(6.45)	(5.54)	(−0.92)	(0.01)
	5 (Near)	1.07	1.27	1.17	1.19	1.32	0.25	0.42
		(4.44)	(6.52)	(6.86)	(7.16)	(7.12)	(2.04)	(3.82)
	5−1						1.28	1.45
							(6.79)	(8.43)

Panel B: Residual IVOL

		Residual IVOL						
		1 (Low)	2	3	4	5 (High)	5−1	4-factor alpha
	1 (Far)	0.11	0.51	0.77	0.92	0.66	0.54	0.47
		(0.36)	(1.62)	(2.63)	(3.06)	(2.06)	(4.50)	(3.89)
	2	0.76	1.05	1.14	1.31	0.97	0.20	0.05
		(2.85)	(4.46)	(4.68)	(5.23)	(3.55)	(2.03)	(0.60)
NH	3	1.08	1.17	1.29	1.37	1.25	0.17	−0.05
		(4.74)	(5.58)	(6.00)	(5.84)	(4.30)	(1.25)	(−0.53)
	4	1.21	1.22	1.36	1.43	1.33	0.11	−0.13
		(6.09)	(6.48)	(7.07)	(6.67)	(4.92)	(0.74)	(−1.08)
	5 (Near)	1.24	1.13	1.31	1.34	1.10	−0.13	−0.41
		(7.50)	(6.69)	(7.02)	(6.51)	(4.29)	(−0.81)	(−3.11)
	5−1						−0.68	−0.88
							(−3.53)	(−5.33)

Table 10. Double-sort Analysis for Returns Excluding the First Five Days of the Month

Table 10 represents the average of monthly raw returns for each double-sorted portfolio. We calculate monthly returns after excluding the first five days of the month. We independently double-sort stocks into 25 portfolios based on the nearness to 52-week high (NH) and the maximum daily returns over the previous month (MAX). We report equal-weighted returns in Panel A and value-weighted returns in Panel B. We also represent the difference in the raw returns and 4-factor alphas between the top and bottom MAX quintile portfolios within each NH quintile portfolio. Additionally, we report the difference in the MAX effect between the top and bottom NH quintiles. We use monthly Fama-French three factors and the Carhart (1997) momentum factor when we calculate 4-factor alphas. Our adjusted t-statistics using the Newey-West (1987) method are reported in parentheses. The sample period is from July 1963 to December 2016.

Panel A: Equal-Weighted Returns

		MAX						
		1 (Low)	2	3	4	5 (High)	5−1	4-factor alpha
	1 (Far)	0.83	0.74	0.50	0.15	−0.47	−1.30	−1.33
							(−8.78)	(−10.43)
	2	0.85	0.84	0.73	0.54	0.11	−0.74	−0.92
							(−5.20)	(−8.46)
NH	3	0.88	0.87	0.88	0.79	0.58	−0.30	−0.53
							(−1.99)	(−5.38)
	4	0.88	0.90	0.95	1.08	0.91	0.02	−0.22
							(0.20)	(−2.14)
	5 (Near)	0.90	0.95	1.05	1.10	1.13	0.23	−0.01
							(1.66)	(−0.15)
	5−1						1.53	1.31
							(11.91)	(10.64)

Panel B: Value-Weighted Returns

		MAX						
		1 (Low)	2	3	4	5 (High)	5−1	4-factor alpha
	1 (Far)	0.77	0.35	0.25	−0.03	−0.50	−1.28	−1.45
							(−5.91)	(−7.17)
	2	0.74	0.43	0.43	0.34	0.09	−0.64	−0.86
							(−3.19)	(−4.94)
NH	3	0.68	0.52	0.54	0.57	0.63	−0.04	−0.25
							(−0.25)	(−1.40)
	4	0.59	0.57	0.71	0.72	0.86	0.27	0.07
							(1.62)	(0.57)
	5 (Near)	0.54	0.64	0.73	0.96	1.08	0.53	0.42
							(3.11)	(2.93)
	5−1						1.81	1.88
							(7.38)	(7.68)

Table 11. Robustness Tests

Table 11 represents robustness test results for various sample selections and the consideration of other stock characteristics. In Panel A, we report the average of monthly MAX strategy profits within each NH portfolio for subperiod samples and excluding NASDAQ samples. In Panel B, we report the average of monthly MAX strategy profits within each NH portfolio for alternative NH definitions. In Panel C, we report the average of monthly MAX strategy profits within each NH portfolio for subsamples by stock characteristics. We consider illiquidity, size, and stock price as stock characteristics. Stocks are first sorted by illiquidity, size, and stock price and grouped into three categories (top 30%, next 40%, and bottom 30%). Then, within each group, they are independently double-sorted into 25 portfolios based on NH and MAX. We also represent the difference in the MAX strategy profits between the top and bottom NH quintile portfolios. We use monthly Fama-French three factors and the Carhart (1997) momentum factor when we calculate 4-factor alphas. Our adjusted t-statistics using the Newey-West (1987) method are reported in parentheses. The sample period is from July 1963 to December 2016.

	NH						
	1 (Far)	2	3	4	5 (Near)	5−1	4-factor alpha
Panel A: Subperiod Samples and Excluding NASDAQ Samples							
1963−1979	−1.93	−0.95	−0.42	−0.08	0.57	2.50	2.32
	(−5.48)	(−2.17)	(−0.99)	(−0.23)	(2.18)	(10.27)	(8.06)
1980−1999	−2.05	−1.19	−0.24	0.36	0.48	2.53	2.28
	(−9.83)	(−5.75)	(−0.76)	(1.02)	(1.40)	(8.84)	(9.19)
2000−2016	−1.59	−1.17	−0.58	−0.21	−0.16	1.43	1.33
	(−4.14)	(−2.72)	(−1.60)	(−0.68)	(−0.65)	(5.69)	(6.38)
Excluding NASDAQ	−1.78	−0.95	−0.36	−0.01	0.35	2.13	1.85
	(−9.01)	(−5.25)	(−2.10)	(−0.07)	(2.46)	(10.93)	(9.91)
Panel B: Alternative NH Definitions							
13-week high	−1.61	−0.79	−0.63	−0.26	−0.44	1.16	0.98
	(−7.83)	(−3.28)	(−2.72)	(−1.22)	(−2.25)	(7.53)	(6.42)
26-week high	−1.92	−0.92	−0.56	−0.12	0.00	1.93	1.68
	(−9.46)	(−4.18)	(−2.46)	(−0.56)	(0.03)	(10.62)	(9.62)
104-week high	−1.54	−1.11	−0.52	0.05	0.42	1.96	1.69
	(−8.26)	(−5.97)	(−2.46)	(0.28)	(2.10)	(9.64)	(9.28)

Table 11. Robustness Tests − Continued

		NH						
		1 (Far)	2	3	4	5 (Near)	5−1	4-factor alpha
Panel C: Subsamples by Stock Characteristics								
	Illiquid	−1.34	−0.72	0.09	0.48	0.51	1.86	1.72
		(−5.78)	(−2.96)	(0.33)	(1.76)	(2.20)	(7.59)	(7.42)
Illiquidity	Medium	−2.11	−1.38	−0.47	0.19	0.42	2.53	2.22
		(−10.03)	(−5.66)	(−2.07)	(0.74)	(2.01)	(10.22)	(9.31)
	Liquid	−2.33	−1.56	−0.99	−0.83	−0.51	1.81	1.56
		(−11.35)	(−8.18)	(−4.57)	(−4.02)	(−2.91)	(7.61)	(6.83)
	Small	−1.95	−1.60	−0.94	−0.39	−0.31	1.64	1.51
		(−9.36)	(−7.36)	(−4.01)	(−1.60)	(−1.68)	(6.94)	(6.50)
Size	Medium	−2.11	−1.32	−0.75	−0.17	0.26	2.38	2.01
		(−9.48)	(−6.24)	(−3.23)	(−0.69)	(1.18)	(9.80)	(8.89)
	Big	−1.43	−0.80	−0.02	0.19	0.25	1.70	1.56
		(−6.49)	(−3.86)	(−0.12)	(0.85)	(1.44)	(7.80)	(7.81)
	Low	−2.85	−2.16	−1.62	−1.00	−0.40	2.44	2.12
		(−12.29)	(−9.88)	(−7.36)	(−3.92)	(−1.77)	(9.22)	(8.42)
Price	Medium	−1.85	−1.18	−0.47	−0.04	0.09	1.94	1.57
		(−9.52)	(−6.21)	(−2.29)	(−0.23)	(0.48)	(9.01)	(7.82)
	High	−1.16	−0.26	0.12	0.27	0.23	1.35	1.25
		(−4.92)	(−1.07)	(0.50)	(1.08)	(1.38)	(6.97)	(6.69)