Why Do Mutual Funds Hold Lottery Stocks?*

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Abstract

We provide evidence of funds holding lottery stocks to gather assets by catering to investor preferences and engaging in risk shifting. These funds are smaller, younger, and poor recent performers – characteristics typically associated with their incentives to attract capital. Employing a difference-in-differences approach, we find that funds with more lottery stocks attract more flows after portfolio disclosure compared to their peers. Funds with higher managerial ownership invest less in lottery stocks and poorly performing funds tend to increase their lottery holdings towards year-ends. Finally, aggregate fund lottery holdings exacerbates the overpricing of lottery stocks.

Keywords: lottery stocks, agency problems, risk shifting, performance, investor flows

JEL Classification: G11, G23.

*We would like to thank Turan Bali, Justin Birru, Kent Daniel, Sandeep Dahiya, Rui Dai, Freda Song Drechsler, Wayne Ferson, Vyacheslav (Slava) Fos, Egemen Genc, Bing Han, Ron Kaniel, Donald Keim, Clark Liu, Pedro Matos, David Mclean, Scott Murray, Sugata Ray, Honglin Ren, Matthew Ringgenberg (discussant), Clemens Sialm, and Xuemin Yan for helpful comments and constructive suggestions. We also benefitted from the comments received at presentations at the Baruch College, the Central University of Finance and Economics, Erasmus University, Georgetown University, Georgia State University, Renmin University, the Tsinghua Finance Workshop, the Indian School of Business, the Indira Gandhi Institute of Development Research, the University of California at Riverside, the University of Houston, the University of North Carolina at Charlotte, the University of Virginia (Darden), and the WRDS Advanced Research Scholar Program at the Wharton School at University of Pennsylvania. Lei Jiang gratefully acknowledges financial support from the AXA Research Fund, the Initiative Research Program supported by Tsinghua University, and the Tsinghua National Laboratory for Information Science and Technology. Vikas would also like to thank the Centre for Financial Research (CFR) in Cologne for their continued support. We thank Linlin Ma and Yuehua Tang for sharing the managerial ownership data.

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1 Introduction

There is abundant evidence that investors have a preference for lottery-like stocks and that these stocks tend to significantly underperform non-lottery-like stocks. A popular explanation is that lottery-like assets have a small chance of a large payoff and investors' strong preferences lead to the overpricing of these assets. Preference for lottery-like payoffs is consistent with cumulative prospect theory (Tversky and Kahneman, 1992; Barberis and Huang, 2008), which predicts the overweighting of the probability of these extremely high returns. Many studies further show that retail investors in particular, have strong preferences for lottery-like stocks (Kumar, 2009; Bali, Cakici, and Whitelaw, 2011; Han and Kumar, 2013). In this study, we provide new evidence that even some institutional investors exhibit significant propensity to hold lottery-like stocks. Specifically, we examine the economic incentives behind some actively managed mutual funds to favor lottery stocks, its implications for fund managers, investors, as well as the cross-sectional lottery stock performance.

Using several commonly used proxies for lottery features of stocks (Kumar, 2009; Bali, Cakici, and Whitelaw, 2011; Bali, Brown, Murray, and Tang, 2017), we measure the lottery holdings at the fund level every quarter through the holding-weighted stock lottery characteristics in the quarter-end month. Even though, on average, about 5% of funds' assets are invested in lottery-like stocks, we find significant cross-sectional variation in funds' propensity to hold lottery stocks (proportion ranges from 1% to 16%). Given the evidence of low expected returns of lottery stocks, it is puzzling that some mutual funds still exhibit high propensity to hold such stocks. To that end, we address four questions in this paper. First, what are the characteristics of funds associated with greater investment in lottery stocks and the implications of holding lottery stocks for a fund's future performance? Second, is holding lottery stocks driven by managers own preference for such stocks or by the preferences of funds' investors? Third, do fund managers use lottery stocks as a way to engage in risk-shifting behavior and benefit from flow-performance convexity in mutual funds? Fourth, what are the asset pricing implications of mutual funds holding lottery stocks for the cross-sectional lottery stock performance?

Our study uncovers several novel findings that shed light on both the incentives of funds

that hold more lottery-like stocks. We show that funds with more lottery holdings have significantly lower *future* returns in the cross-section, which is consistent with well-established evidence that lottery stocks are overpriced and that they earn lower future returns (Barberis and Huang, 2008; Bali, Cakici, and Whitelaw, 2011). Given the detrimental effect of holding lottery stocks on fund performance, a natural followup question is: why do *some* fund managers invest a significant proportion of funds' assets in such stocks? There can be several potential explanations for this behavior. First, mutual fund managers may hold lottery stocks to cater to their investors' preferences for such stocks and attract more flows. Second, it is possible that managers themselves may exhibit similar preferences. Finally, agency problems in mutual funds can be associated with risk-shifting behavior where managers may increase the riskiness of their funds towards the end of the year. Buying lottery stocks can be a way for the managers to increase their chances of winning by the end of the year and beating their peers.

Although investors' preferences are not directly observable, we follow Barber, Huang, and Odean (2016) and Berk and van Binsbergen (2016) and use net flows as a proxy for the revealed preference of mutual fund investors. We find that funds with higher lottery holdings are smaller in size, younger, and have poor past performance. All of these characteristics are consistent with such funds having more incentives to cater to the lottery preferences of their investors to attract flows. As a result, we hypothesize that funds with high lottery holdings may attract more net flows after controlling for funds' past performance and other fund characteristics. To test this prediction, we estimate piecewise linear regression of flows following Sirri and Tufano (1998). We find that even after controlling for past performance and other fund characteristics, funds holding more stocks with lottery features receive more net flows from their investors. This result holds both for funds with institutional clientele and for funds with retail clientele, although the significant flow effect is more pronounced for funds with more retail clientele.[1] This evidence of retail investors opting for exposure to

[1]That institutional investors also exhibit preference for, and not aversion to lottery-like stocks, may appear surprising. However, recent evidence suggests otherwise. For example, Edelen, Ince, and Kadlec (2016) show that institutional investors have a strong tendency (i.e., agency-induced preferences) to seek characteristics associated with the short leg of anomalies (e.g., stocks with high growth assets or high net equity or debt issuance), since these characteristics offer a tangible identification of good companies (though

lottery stocks indirectly through mutual funds complements prior studies documenting retail investors' direct investments in lottery stocks (Kumar, 2009; Kumar, Page, and Spalt, 2011; Doran, Jiang and Peterson, 2012; Han and Kumar, 2013; Bali et al., 2017).

Our findings are also economically significant. Ceteris paribus, a one-standard-deviation increase in lottery holdings during a quarter is associated with a 15% to 35% increase in fund flows (relative to total net assets) in the next quarter for funds with institutional investors, depending on the measure of lottery holdings. For funds with retail investors, this number is even higher, between 20% and 45%. Our results therefore suggest that funds hold lottery-like stocks to attract flows by capitalizing on investors' preference for such stocks. The effect of lottery holdings on investor flows is distinct from investors chasing growth stocks (Frazzini and Lamont, 2008) and recent winners (Agarwal, Gay, and Ling, 2014), investor overweighting the extreme positive payoffs of fund returns (Akbas and Genc, 2018; Goldie, Henry, and Kassa, 2018), as well as investors with tail overweighting preference (Polkovnichenko, Wei, and Zhao, 2019). These findings are robust to the use of alternative measures of lottery holdings such as the proportion of lottery stocks held by funds and the holding-weighted lottery measure for the top 10 stocks held by funds, since fund investors may respond more to the top fund holdings that are easily observable through different sources such as fund websites and leading fund rating agency, Morningstar. Finally, our findings are also robust after including fund holding characteristics related to value or growth, window dressing measures, as well as funds' past performance and extreme positive payoffs. Overall, this evidence collectively suggests that investors acquire information on funds' portfolio holdings and allocate capital to funds with more lottery stocks.

To further investigate that lottery holdings attract flows, we first zoom into the period around the filing dates on which funds disclose their portfolios. If the flow effect is truly driven by funds' lottery holdings, we expect to observe higher flows only after the filing dates, when the underlying holdings become visible to the investors. Using monthly flow data from CRSP and filing dates from the Securities and Exchange Commission (SEC) EDGAR

evidently bad investments). Akbas, Armstrong, Sorescu, and Subrahmanyam (2015) show that mutual funds disproportionately purchase stocks that are already overvalued, and therefore mutual fund flows exacerbate cross-sectional mispricing.

database, we employ a difference-in-differences (DID) approach and find that funds with more lottery holdings attract significantly more flows only after the month of filing, and there is no significant difference between the average monthly flows for the treatment and control groups through the pre-disclosure periods. Moreover, using daily flow data from Trimtabs, we further confirm significantly greater flows only after the filing dates. Taking together, these results are suggestive that funds with more lottery holdings attract significantly higher flows, especially after the filing dates when funds disclose their portfolio holdings. This finding adds to the existing research, which indicates that investor flows respond to the characteristics of disclosed portfolio holdings, above and beyond funds' past performance or extreme performance (Frazzini and Lamont, 2008; Agarwal, Gay, and Ling, 2014; Akbas and Genc, 2018; Goldie, Henry, and Kassa, 2018).[2]

In addition to fund managers catering to the preferences of their investors, it is possible that managers themselves exhibit preference for such stocks. For instance, Edelen, Ince, and Kadlec (2016) show that agency-induced preferences can explain the tendency of institutional investors to buy overvalued stocks that comprise the short leg of anomalies. Brown, Lu, Ray, and Teo (2018) show that sensation-seeking hedge fund managers often take higher risks and exhibit preferences for lottery-like stocks. A contrasting view is that institutional investors are considered to be "smart" and sophisticated, and therefore should avoid holding lottery stocks. To disentangle between managers' and investors' lottery-type preferences, we investigate how portfolio manager ownership affects a fund's tendency to invest in lottery-like stocks. We find that managers tend to avoid lottery-like stocks when their ownership in the funds is high. We interpret this evidence as being inconsistent with managers' own preference for lottery stocks.

We conduct further tests examining seasonality in funds' tendency to hold lottery stocks. We hypothesize that agency problems in mutual funds can be associated with risk-shifting behavior where managers may increase lottery holdings with the hope of "winning the lottery" (i.e., achieving high returns) towards the end of the year.[3] This hypothesis is predicated on

[2]This evidence does not necessarily imply irrationality, since rational investors can use holdings information as an ex ante measure of managerial ability in conjunction with past performance, which is an ex post measure.

[3]This literature includes the window-dressing behavior among portfolio managers (e.g., Lakonishok et

two arguments. First, the literature on tournaments and the convexity in flow-performance relation (e.g., Brown, Harlow, and Starks, 1996; Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Huang, Wei, and Yan, 2007) suggests that investors typically evaluate funds on a calendar-year basis and funds that perform well on an annual basis receive disproportionately higher flows than their peers. This, in turn, can incentivize poorly performing funds to increase their risk towards the end of the year to beat their peers. Second, buying lottery stocks can be a way for the managers to increase their chances of winning by the end of the year. We find that managers with poor performance earlier in the year tend to increase their positions in lottery stocks towards year ends, consistent with risk-shifting behavior of fund managers to outperform their peers.

Finally, we explore the asset pricing implications of mutual funds holding lottery stocks. Flows to mutual funds have been shown to create distortions in capital allocation across stocks. When mutual fund managers receive new flows from investors they usually increase positions in existing stock holdings, as a result, net money inflows are associated with higher contemporaneous returns of those stocks and subsequent return reversal (Coval and Stafford, 2007). Consistent with this prediction, Akbas et al. (2015) show that there is a negative relation between aggregate flows to mutual funds and returns to proxies of mispricing factor, indicating that mutual fund flows exacerbate cross-sectional mispricing. Motivated by these findings, we hypothesize that if mutual funds disproportionately purchase lottery stocks that are already overvalued, and if the resulting price pressure further exacerbates these stocks' overvaluation, we would expect these stocks to experience a price reversal following higher aggregate lottery holdings by mutual funds. Supporting this notion, we find that higher aggregate fund lottery holdings imply a more negative lottery demand factor return in the stock market, consistent with more pronounced underperformance of lottery stocks in the

al., 1991; He, Ng, and Wang, 2004; Ng and Wang, 2004;, and Agarwal, Gay, and Ling, 2014), strategic risk-shifting motivated by agency issues (e.g., Brown, Harlow, and Starks, 1996; Chevalier and Ellison, 1997; Kempf and Ruenzi, 2008; Kempf, Ruenzi, and Thiele, 2009; Hu et al., 2011; Huang, Sialm, and Zhang, 2011; and Schwarz, 2012), conflict of interests arising from offering multiple products (e.g., Gaspar, Massa, and Matos, 2006; Chen and Chen, 2009; Cici, Gibson, and Moussawi, 2010; Bhattacharya, Lee, and Pool, 2013) and incentive misalignment due to business ties (e.g., Davis and Kim, 2007; Cohen and Schmidt, 2009; and Ashraf, Jayaraman, and Ryan, 2012).

cross-section.[4]

Our analysis contributes to several streams of research. First, our findings contribute to the literature on the clientele effect of lottery-like stocks. Kumar (2009), Bali, Cakici, and Whitelaw (2011), and Han and Kumar (2013) show that retail investors, particularly, have a preference for lottery-like stocks. In contrast, our study emphasizes that even some institutional investors such as active mutual funds hold stocks with lottery features and explores their motives behind holding such stocks. In addition, our study uncovers a new channel, namely investing in lottery stocks, through which mutual funds can engage in risk-shifting behavior.

Finally, our study provides new evidence on the asset pricing implications of mutual funds holding lottery stocks. We show that higher aggregate fund lottery holdings imply a more negative lottery demand factor return and exacerbate the overpricing of lottery stocks in the cross-section, which complements previous studies on flows to mutual funds creating distortions in capital allocation across stocks (Coval and Stafford, 2007; Akbas et al., 2015).

The structure of rest of paper is as follows. Section 2 describes the data and variables used in our empirical analyses. Section 3 sheds light on the relation between funds' characteristics and lottery holdings and its impact on the cross-section of fund returns. Section 4 discusses different economic explanations regarding the incentives of funds to hold lottery stocks. Section 5 explores the asset pricing implications of mutual funds holding lottery stocks. Section 6 concludes.

2 Data and Variable Construction

2.1 Data

We obtain fund return data and fund characteristics such as expense ratio, turnover ratio, total net assets (TNA), family size, and fund age (oldest share class in the fund) from the Center for Research in Security Prices (CRSP) Survivorship Bias Free Mutual Fund Database.

[4]We obtain the lottery demand factor return based on Bali et al. (2017), who generate a factor capturing the returns associated with lottery demand and examine the time-series properties of the factor.

Our sample periods starts in January 2000 since we require daily fund returns for some of our analysis, and ends in December 2014.[5] The size of a fund family is the sum of total assets under management of all funds in the family (excluding the fund itself). Return, turnover ratio, and expense ratio are the TNA-weighted average across all fund share classes. Monthly fund flows are estimated as the change of TNA from month to month (excluding the change in asset size due to fund return). We base our selection criteria on the objective codes from the CRSP mutual fund data following Kacperczyk, Sialm, and Zheng (2008). We drop ETFs, annuities, and index funds based on either indicator variables or fund names from the CRSP data. Since our focus is on equity funds, we require 70% of assets under management to be in stocks. We restrict our sample to funds that are at least a year old and have at least $20 million in assets, and use the date of creation of the fund ticker to control for the incubation bias documented in Evans (2010). We use net-of-fee fund returns to focus on the actual performance experience of investors.

We obtain each fund's investment objective code and share volume of portfolio holdings from the Thomson Reuters Mutual Fund Holdings (formerly CDA/Spectrum S12) database. Using the holding value as the weight, we calculate the fund-level stock holding characteristics from the CRSP and Compustat datasets, including market capitalization, book-to-market ratio (supplemented by book values from Ken French's website), and past six-month cumulative return (Jegadeesh and Titman, 1993) for all common stocks listed on the NYSE, AMEX, and NASDAQ. We adjust trading volume for stocks with CRSP share codes 10 or 11 in NASDAQ as in Gao and Ritter (2010) to avoid double counting associated with trades with market makers and trades among market makers. We remove funds with an investment objective code of 1, 5, 6, 7, or 8, which stand for International, Municipal Bonds, Bond and Preferred, Balanced, and Metals funds, respectively. We require funds to hold more than 10 stocks to be included in our sample. We merge the CRSP Mutual Fund database and the Thomson Reuters Mutual Fund Holdings database using the MFLINKS tables provided by the Wharton Research Data Services (WRDS).

[5] Although mutual fund holdings data are available beginning in January 1980, our sample period starts in January 2000 since we require daily fund return data to estimate funds' daily four-factor alphas and maximum daily returns (MAX^{Fund}). In addition, for some of our tests, we need to control for fund volatility during the year, which we estimate using past one-year daily returns as in Jordan and Riley (2015).

Finally, for a more in-depth analysis on the timing of capital flows, we use data on both monthly flows from CRSP Survivorship Bias Free Mutual Fund Database and daily flows from TrimTabs. There are tradeoffs between using these two databases. While CRSP provides a much more comprehensive coverage of the mutual fund universe, fund flows can only be *estimated* using TNA and returns, at best, on a monthly basis. In contrast, Trimtabs provides *actual* net flows (in dollars) and total net asset (TNA) at a much higher daily frequency. The daily flows from Trimtabs are therefore not subject to measurement error as in the case of flows imputed from funds' assets and returns.[6] However, TrimTabs dataset relies on voluntary disclosure by mutual funds and therefore has limited coverage of the funds compared with CRSP sample. To precisely identify the time when funds' portfolio holdings become available to investors, we follow Schwarz and Potter (2016) to obtain the actual filing dates of funds' holdings.[7]

2.2 Measures of lottery characteristics

Following Bali, Cakici, and Whitelaw (2011) and Bali et al. (2017), we use two measures for a stock's ex-ante lottery-like features; MAX and $MAX5$, calculated as the maximum daily return and the average of the five highest daily returns of the stock within a month, respectively. These measures reflect the upside potential an asset has compared with others. Assets with higher MAX and $MAX5$ indicate higher upside potential, and investors are willing to pay a premium for holding such assets, which implies lower expected returns. We construct the holding-weighted lottery characteristics to obtain a fund-level measure of lottery holdings: MAX^{Hold} and $MAX5^{Hold}$.[8]

Table 1 reports the summary statistics and correlation coefficients of the key variables

[6]Following Greene and Hodges (2002), Rakoswski (2010), and Kaniel and Parham (2017), we calculate the daily fund flows as the ratio of dollar flows to prior day's total net assets.

[7]We thank Chris Schwarz for providing this data at http://schwarzpottermfdata.com/.

[8]For robustness, we use three alternative lottery holding measures based on (i) the ratio of the value of lottery stocks and that of all stocks for the fund at quarter end, which captures the percentage of a fund's assets invested in lottery stocks; (ii) the holding-weighted lottery measure for the top 10 stocks held by the fund based on the holding values; and (iii) the composite lottery index of lottery-likeness following Kumar (2009) and Bali, Hirshleifer, Peng, and Tang (2018). The correlations between MAX^{Hold} or MAX5^{Hold} and the other lottery holding proxies are high, ranging between 0.81 and 0.87. As shown in the Sections A.1 and A.2 in the Internet Appendix, our results are similar when we use these alternative measures.

used in the empirical analysis. Our final sample comprises 115,655 fund-quarter observations for 3,066 funds. In Panel A of Table 1, we report summary statistics for the lottery holding measures and observe that the mean values for MAX^{Hold} and $MAX5^{Hold}$ are 4.58% and 2.77%, respectively. The figure of 4.58% implies that funds' stock holdings on average have a maximum daily return of 4.58% in a month. A similar interpretation applies to the figure of 2.77% computed using the average of the five highest daily returns of all stocks held by the fund. To put these figures in perspective, they are quite large since during the same period from January 2000 to December 2014, the average daily return for common stocks listed on NYSE, AMEX, and NASDAQ is only 0.07%.

[Table 1 about here]

2.3 Other key variables

Panel B of Table 1 also reports summary statistics for the other key variables. We define alpha as the quarterly percentage alpha estimated from the Fama-French-Carhart four-factor model using fund daily returns within a quarter. Panel B shows that the mean (median) quarterly alpha is −0.49% (−0.31%). The average fund TNA is $1,279 million and the average fund age is 14.8 years. The average annual expense ratio is about 1.2%. The average annual turnover ratio as reported in the CRSP data is 86.2%. Finally, funds' average quarterly flow is 1.89%.

Panel C of Table 1 provides the correlations between the key variables. Not surprisingly, the two lottery holding measures are strongly correlated with a positive coefficient of 0.89. For brevity, we use MAX^{Hold} as our principal measure of lottery holdings. Our results are robust to the use of the alternative lottery holding measure, $MAX5^{Hold}$. We also find that the lottery holding measures are negatively related to fund size and age, and positively related to expense ratio and portfolio turnover.

3 Empirical Results

3.1 Fund characteristics associated with lottery holdings

To examine the fund characteristics associated with holding lottery stocks, we form decile portfolios of funds based on their lottery holdings at the beginning of each calendar quarter. Decile 1 contains funds with the lowest lottery holdings and decile 10 contains funds with the highest lottery holdings. Since funds report their holdings on a fiscal quarter basis instead of a calendar quarter, following prior literature (e.g., Schwarz, 2012), we assume that the portfolio holding shares remain unchanged since the last report date of the holdings until new holding information releases. For example, if a fund has two consecutive fiscal quarters ending on February 28 and May 31, we assume that the portfolio at the calendar quarter-end of March is the same as that on February 28, and the portfolio at the calendar quarter-end of June is the same as that on May 31.

Table 2 shows the cross-sectional averages of various characteristics of fund portfolios in the portfolio formation quarter. Panel A shows that funds in the high MAX portfolio (decile 10) have an average lottery holding measure of 7.08%, implying that their stock holdings on average have a maximum daily return of 7.08%. For funds in the lowest MAX decile portfolio (decile 1), the average lottery holdings measure is 3.16%.[9] The average fund size for the low MAX funds is \$1.84 billion, compared with \$668 million for the high MAX funds. The average high MAX fund is more than five years younger than the average low MAX fund, charges 0.26% more in expenses per year, and has a higher annual turnover of 118% (versus 62% for the low MAX funds).

[Table 2 about here]

Funds with low lottery holdings exhibit different factor loadings compared to their counterparts. Panel B of Table 2 shows that high MAX funds have significantly higher market

[9] To further understand the economic significance of the cross-sectional variation in lottery holdings, Table A.1 in the Internet Appendix shows the summary statistics for alternative lottery holding measures. Panel A of Table A.1 shows that on average, the proportion of fund's assets that is invested in lottery stocks ($MAXProp$) is 5%. However, Panel B of Table A.1 shows large cross-sectional variation in lottery holdings. Specifically, funds in the high $MAXProp$ (decile 10) on average invest 16% of their assets in lottery stocks, while the number for funds in the low $MAXProp$ (decile 1) is only 1%.

exposure (β^{MKT}), more small cap exposure (β^{SMB}), lower value exposure (β^{HML}), and more momentum exposure (β^{UMD}) than low MAX funds. Funds in the highest MAX decile portfolio perform significantly much worse, with an average 4-factor quarterly alpha of -1.02%, compared to -0.14% for funds in the lowest MAX decile portfolio. Panel C shows similar results when we examine characteristics of stocks in funds' portfolio instead of the factor exposures. We find that high MAX funds are more likely to hold small cap, growth, and momentum stocks compared with low MAX funds.

Is the heterogeneity in lottery holdings shown in Panel A simply due to the differences in the funds' investment styles? To explore this possibility, we investigate the cross-sectional variation in lottery holdings of mutual funds within each investment style. We classify funds into various investment styles based on the Lipper investment categories from the CRSP mutual fund data available from June 1998. The objective codes include: (i) Mid-Cap, (ii) Small-Cap, (iii) Micro-Cap, (iv) Growth, and (v) Growth and Income. Panel D shows that the heterogeneity in lottery holdings is not concentrated in a particular fund style and is pervasive across all investment styles. For example, across each style, funds in the highest MAX decile portfolio have significantly more lottery holdings than funds in the lowest MAX decile portfolio, with t-statistics of the high minus low portfolio ranging from 9.18 to 11.67. The differences in lottery holdings are most pronounced in the micro-cap and growth funds; however, they are also present in the small- and mid-cap funds, as well as in the growth and income funds. Therefore, cross-sectional variation in funds' lottery holdings is not entirely driven by funds' investment styles.

3.2 Lottery holdings and future fund performance

In this section, we investigate the predictive power of fund lottery holdings on future fund performance. Lottery-like stocks are known to underperform in the future since investors are willing to pay for a premium for holding such stocks, i.e., they are priced higher and offer lower expected returns (Bali, Cakici, and Whitelaw, 2011). However, the implications of holding lottery stocks for future fund performance is not clear ex ante. On one hand, mutual funds hold diversified portfolios that can attenuate the effect on fund performance. On the

other hand, it is likely that the lottery features of stocks are not easy to diversify away, and a portfolio of lottery stocks also exhibits lottery-like payoffs (Bali, Brown, Murray, and Tang, 2017). To explore these possibilities, we examine the cross-sectional relation between lottery holdings and future performance at the individual fund level in Sections A.1 – A.3 of the Internet Appendix. Using both univariate portfolio sorts and Fama-MacBeth regressions to control for fund-specific characteristics, we show that higher funds' lottery holdings imply lower future performance, which is consistent with well-established evidence that lottery stocks are overpriced and that they earn lower future returns (Barberis and Huang, 2008; Bali, Cakici, and Whitelaw, 2011).

Specifically, Table A.2 of the Internet Appendix shows that funds in the lowest MAX decile generate 4.80% higher risk-adjusted returns per annum (using net-of-expense returns) than funds in the highest MAX decile, using a univariate portfolio-level analysis. Morever, Table A.3 shows that funds with more lottery holdings significantly underperform in the future and this result is robust after controlling for a large number of fund characteristics and other predictors of fund performance. Table A.4 shows that the univariate portfolio-level results are i) not driven by small funds, and ii) robust to the use of holding-based performance measure such as the characteristic-adjusted returns in Daniel, Grinblatt, Titman, and Wermers (DGTW) (1997), and iii) pervasive across various investment styles, and iv) robust to the use of three alternative lottery holding measures.[10] Finally, we address a potential concern that the predicability of lottery holdings for funds' performance is attributable to other predictors identified in the prior literature. In Table A.5 of the Internet Appendix, we conduct a conditional bivariate portfolio test for lottery holdings by controlling for known measures of manager skill such as the return gap, active share, and R-squared. Our results continue to show that lottery holdings have significant predictive power for the cross section

[10]The first measure, $MAXProp$, is the proportion of fund's assets that is invested in lottery stocks (i.e., stocks whose MAX is in the top quintile among all stocks). The second measure, $Top\ 10\ MAX^{Hold}$, is the holding-weighted lottery measure (i.e., MAX of the stocks) for the top 10 stocks held by the funds based on their investments. We focus on the top 10 stocks because when faced with a long list of fund holdings, investors may only respond to the top holdings of a fund. The third measure, the lottery index ($LTRY$), is a composite index of lottery-likeness following Kumar (2009) and Bali, Hirshleifer, Peng, and Tang (2018), who define lottery-like stocks as those with low-price, high idiosyncratic volatility, and high idiosyncratic skewness.

of future fund returns.

4 Economic Explanations for Holding Lottery Stocks

In the previous section, we show that funds holding more lottery stocks significantly underperform in the future compared with funds holding fewer lottery stocks. Given the detrimental effect of holding lottery stocks on fund performance, a natural question is: why do those funds hold lottery stocks, i.e., what are their economic incentives? There can be several reasons for this behavior. First, fund managers may hold lottery stocks to cater to their investors' preferences for such stocks. Second, it is possible that managers themselves may exhibit similar preferences. Finally, agency problems in mutual funds can be associated with risk-shifting behavior where managers may increase their risk towards the end of the year. Buying lottery stocks can be a way for the managers to increase their chances of winning by the end of the year and beating their peers. In this section, we examine these different possibilities to understand why some mutual funds invest significantly in lottery stocks.

4.1 Do funds' lottery holdings attract flows?

In this section, we examine the first possibility that mutual funds hold lottery stocks to cater to the preferences of their investors. To test this possibility, we investigate how fund investors react to a fund's tendency to hold lottery stocks after controlling for fund's past performance. In particular, the tendency to hold stocks with lottery-features may bring additional flows by attracting investors who have preferences for stocks with lottery-like characteristics (Kumar, 2009; Bailey, Kumar, and Ng, 2011). Prior studies document that the characteristics of stocks included in mutual fund portfolios can help predict fund performance.[11] One potential explanation is that holdings can provide ex-ante information about managerial ability in contrast to the ex-post information from past performance. Moreover, there is evidence that

[11] See, for example, Grinblatt and Titman (1989, 1993); Grinblatt, Titman, and Wermers (1995); Daniel et al. (1997); Wermers (1999, 2000); Chen, Jegadeesh, and Wermers (2000); Gompers and Metrick (2001); Cohen, Coval, and Pastor (2005); Kacperczyk, Sialm, and Zheng (2005, 2008); Sias, Starks, and Titman (2006); Jiang,Yao, and Yu (2007); Kacperczyk and Seru (2007); Cremers and Petajisto (2009); Baker et al. (2010).

fund investors respond to the information in fund portfolios after controlling for funds' past performance. For example, Frazzini and Lamont (2008) show that retail investors tend to direct "dumb" money into mutual funds that hold growth stocks and out of funds holding value stocks, and earn lower returns by holding these overvalued stocks. Solomon, Soltes, and Sosyura (2014) show that media coverage of mutual fund holdings affects how investors allocate money across funds. Agarwal, Gay, and Ling (2014) show that window dressers who buy winners and sell losers benefit from higher investor flows compared with non-window dressers, conditional on good performance during the period between the portfolio holding date and filing date. Harris, Hartzmark, and Solomon (2015) find that funds that "juice" up their returns by buying stocks before dividend payments attract more flows from their investors, especially retail ones.

We use a piecewise linear specification to capture the previously documented nonlinear flow-performance relation (Ippolito, 1992; Chevalier and Ellison, 1997; Sirri and Tufano, 1998). Specifically, for each quarter we sort all funds according to their risk-adjusted performance (the Fama-French-Carhart four-factor alpha) and assign them fractional ranks uniformly distributed between 0 (worst performance) and 1 (best performance). These ranks represent a fund's percentile performance relative to other funds over the previous quarter. The variable $Low_{i,t}$ for each fund i is defined as $Min(0.2, RANK_{i,t})$, while $Mid_{i,t}$ is defined as $Min(0.6, RANK_{i,t} - Low)$. Finally, $High_{i,t}$ is defined as $RANK_{i,t} - Low - Mid$:

$$\begin{aligned} Flow_{i,t+1} &= \lambda_0 + \lambda_1 \cdot Lottery\ Holdings_{i,t} + \lambda_2 \cdot Low_{i,t} + \lambda_3 \cdot Mid_{i,t} + \lambda_4 \cdot High_{i,t} \\ &\quad + \sum_{k=1}^{K} \lambda_k \cdot Fund\ Controls_{k,t} + \epsilon_{i,t+1.} \end{aligned} \tag{1}$$

where the dependent variable is the quarterly percentage net flow during the lead quarter.[12] Our primary variable of interest is *Lottery Holdings*, which we proxy by the average MAX^{Hold}

[12] Although SEC regulation allows funds to disclose holdings at the end of the quarter with a maximum delay of up to 60 days, many funds do not significantly delay reporting their holdings. Therefore, we focus on the one-quarter-ahead net flows in quarter $t+1$. To address the concern that some funds may further delay reporting their holdings, following Agarwal, Vashishtha, and Venkatachalam (2018), we also repeat our analysis using the average net flows during quarter $t+1$ and $t+2$. Our results remain similar.

during the current quarter. Other fund controls include the natural log of total net assets (TNA), flows, natural log of age, expense ratio, turnover ratio, and natural log of the fund family's TNA, all measured as of the end of quarter t. To ease interpretation of the results, we standardize all continuous independent variables to z-scores by demeaning them and then dividing them by their respective standard deviations. We estimate the model with both time and fund fixed effects, and cluster the standard errors at the fund level.

[Table 3 about here]

Table 3 presents the results. Consistent with existing studies, in all specifications we find a strong relation between net flows and past performance. More relevant for our study, Panel A of Table 3 shows that the lottery holdings of mutual funds influence flows, after controlling for funds' past performance. Model (1) shows that funds that hold stocks with high MAX attract more flows. The magnitude is also economically significant: a one standard deviation increase in MAX^{Hold} in model (1) is associated with a 0.65% increase in fund flows in the following quarter (roughly a 35% increase for the average fund). More importantly, in model (1), our results are robust to controlling for the extreme positive payoffs of fund returns, proxied by the maximum fund daily return (MAX^{Fund}).[13] In addition, our results are robust to controlling for the proportions of winners and losers in funds' disclosed portfolios, and we find evidence consistent with Agarwal, Gay, and Ling (2014), who show a significantly positive (negative) relation between the winner proportion (loser proportion) and fund flows.[14] The findings in model (1) support the notion that investors respond to a fund's lottery holdings over and above a fund's average performance, extreme payoffs, and winner/loser holdings.[15]

Next, we use an alternative lottery holding measure, $MAXProp$, defined in Section 3.2,

[13]Akbas and Genc (2018) show that fund investors may overweight the probability of high payoff states and direct more flows to these type of funds.

[14]In the spirit of Agarwal, Gay, and Ling (2014), we create quintiles of all domestic stocks in the CRSP stock database by sorting stocks in ascending order according to their returns over the past three months. The first (fifth) quintile consists of stocks that achieve the lowest (highest) returns. Then, using each fund's reported holdings, we identify stocks that belong to different quintiles and calculate the proportions of the fund's assets invested in the first quintile ($LoserProp$) and the fifth quintile ($WinnerProp$).

[15]Lottery stocks are not necessarily winner stocks. Winner stocks are those with highest cumulative three-month returns as in Agarwal, Gay, and Ling (2014), whereas lottery stocks are ones with the highest daily returns in the quarter-end month. Consistent with this distinction, the correlation between the fund-level proportion of lottery stocks and the proportion of winners is low at 0.17.

and examine how it is related to fund flows. We also focus on the other alternative lottery holdings measure, $Top\ 10\ MAX^{Hold}$, because limited attention of investors may affect fund holdings' informativeness and investors may only respond to stocks with high visibility. Model (2) reports the results using $MAXProp$ as an independent variable. Consistent with our prediction, the coefficient on $MAXProp$ of 0.24 is statistically and economically significant (t-stat. $= 2.62$) indicating that funds with a one standard deviation increase in the proportion of lottery stocks attract 0.24% higher quarterly flows. Model (3) yields similar results when we replace $MAXProp$ in model (2) with $Top\ 10\ MAX^{Hold}$ to focus on the lottery stocks in the top ten holdings of the funds.[16]

Finally, following Evans and Fahlenbrach (2012) and Barber, Huang and Odean (2016), we distinguish a fund's clientele if a fund is broker-sold (direct-sold), representing unsophisticated (sophisticated) investors.[17] Since lottery preference of unsophisticated (retail) investors is likely to be stronger than that of sophisticated (institutional) investors, we expect a stronger flow response of broker-sold funds to lottery holdings compared with direct-sold funds. Panel B of Table 3 reports the results separately for funds with retail and institutional clientele using specifications similar to those in Panel A. We find that the significant flow effect is more pronounced for funds with more retail clientele. The differences in coefficients on lottery holdings between retail and institutional funds are in the range of 0.12 and 0.22 and statistically significant, indicating that funds with more retail clientele attracts 6% to 12% additional flows compared to funds with more institutional investors.[18]

[16]Significant flow results here are not simply capturing the effect of "attention-grabbing" stocks with media coverage documented in Fang, Peress, and Zheng (2014). While they find evidence that due to limited attention and shortage of cognitive resources, managers tend to buy stocks covered by mass media or "attention-grabbing" stocks and these stocks underperform in the future, they do not find evidence that these types of stocks attract higher fund flows. In addition, stocks can be in the media coverage for many other reasons beyond being lottery stocks, such as firms being involved in M&As or other corporate events.

[17]This proxy of investor sophistication level distinguishes between a direct-sold versus broker-sold distribution channel. Related studies include Chalmers and Reuter (2013), who show that investors who purchase mutual funds through a broker tend to be less well educated than investors who buy funds directly sold by fund companies. Del Guercio and Reuter (2013) find that flows for direct-sold funds are more sensitive to alphas. Barber, Huang, and Odean (2016) find that investors of direct-sold funds use more sophisticated models to assess fund manager skill rather than investors in broker-sold funds.

[18]In untabulated tests, we conduct a similar analysis at the share class level by separating retail shares from institutional shares as in Chen, Goldstein, and Jiang (2010). We continue to find evidence that the significant flow effect is more pronounced for the retail share class than the institutional share class, consistent with retail investors having stronger demand for lottery-like holdings of mutual funds.

4.2 Daily and monthly flow responses to funds' holdings disclosure

In the previous section, we show that the lottery features of the underlying individual stocks of mutual funds attract flows, especially from the retail investors. The underlying assumption behind this mechanism is that investors are able to observe funds' holdings or at least part of the holdings (e.g., top 10 holdings). This is plausible given that investment advisory firms periodically file their current holdings in forms N-30D, N-Q, N-CSR, and N-CSRS with the SEC. Recent studies show that institutional investors use such filing information to make their investment decisions (Chen et al., 2018; Crane, Crotty, and Umar, 2018). For a more in-depth analysis on the timing of capital flows, we zoom into the period around the filing dates on which funds disclose their portfolios and compare the flows before and after the filing dates. We expect to observe higher flows after the filing dates for funds with high lottery holdings when the holding information becomes visible to and accessible by investors. To precisely test this prediction, we use daily flow data from the Trimtabs database that has been used previously in Greene and Hodges (2002), Rakoswski (2010), and Kaniel and Parham (2017).[19] We employ a difference-in-differences (DID) approach. The key assumption behind the DID methodology is that, in the absence of treatment (i.e., lottery holdings), the average change in the response variable (daily flows) would have been the same for both the treatment and control groups. As a result, we implement DID as an interaction term between time (post filing date) and treatment group dummy in the following regression:

$$flow_{i,t} = \beta_0 + \beta_1 \times I(treat_{i,t}) + \beta_2 \times I(post_{i,t}) + \beta_3 \times I(treat_{i,t}) \times I(post_{i,t}) + \epsilon_{it}, \qquad (2)$$

where $I(treat) = 1$ if the fund has the highest lottery holdings ranked among the top 20% of funds and $I(treat) = 0$ if the fund has the lowest lottery holdings ranked among the bottom 20% of funds, observed six weeks before ($I(post) = 0$) and six weeks after ($I(post) = 1$) the filing date. Here β_3 is the parameter of interest (i.e., the DID estimator). We use a six-week period around the filing date to evenly split the period between two consecutive quarterly

[19] Consistent with Kaniel and Parham (2017), we find that the coverage in the Trimtabs varies from about 6% of fund share classes at the beginning of our sample period (the year 2000) to approximately 24% at the end of the year 2014. To address the potential concern of limited coverage, in this section we also repeat the flow analyses based on Eq. (2) using monthly flows from the CRSP sample and find similar results.

disclosures. Our results are not sensitive either to the cutoffs to define the treatment and control groups, or to the choice of the pre- and post-disclosure periods.

Panel A of Table 4 shows that the coefficient on β_1 is not statistically significant, indicating that there is no difference between the average daily flow for treatment and control groups during the pre-treatment period. However, the coefficient β_3, which is the variable of interest, is 0.125% and highly significant with a t-statistic of 6.28, showing that funds with more lottery holdings attract 0.125% higher daily flows than those ranked in the bottom after portfolio disclosure date. This finding is also economically meaningful as the average daily flows are 0.018% in our sample.

[Table 4 about here]

The TrimTabs dataset relies on voluntary disclosure by mutual funds and therefore has limited coverage of funds compared to the CRSP database. To address this potential concern, we repeat the flow analyses based on Eq. (2) using monthly flows from the CRSP sample that has the comprehensive coverage of funds. We use a one-month period around the filing month to evently split the period between two consecutive quarterly disclosures. Panel B of Table 4 shows similar results using the CRSP sample as those in Panel A which relies on the Trimtabs dataset. Again, the coefficient β_3, is 0.18 and highly significant, showing that funds with more lottery holdings attract 0.18% higher monthly flows than those ranked in the bottom after portfolio disclosure month. This finding is also economically meaningful as the average monthly flows are 0.60% in the CRSP sample. These results suggest that the flow results in Panel A do not only apply to a limited sample of funds in the TrimTabs dataset, but also to a broader sample of funds in the CRSP data. Overall, the findings in Table 4, combined with those in Table 3, are suggestive that funds with more lottery holdings attract significantly more flows, especially after the filing dates when funds disclose their portfolio holdings.

4.3 Why do investors respond to lottery holdings?

Our results in the previous section show that investor flows respond to the characteristics of disclosed portfolio holdings (MAX^{Hold}), above and beyond funds' past performance or extreme performance. This evidence does not necessarily imply irrationality, since rational investors can use holdings information as an ex ante measure of managerial ability in conjunction with past performance, which is an ex post measure. In recent studies, Akbas and Genc (2018) and Goldie, Henry, and Kassa (2018) show that funds with high daily maximum returns (MAX^{Fund}) attract more flows, consistent with investors overweighting the probability of funds' extreme payoffs. In this section, we distinguish the ex ante measure of performance (MAX^{Hold}) from the ex post measure of managerial ability (MAX^{Fund}) by investigating their predictive power for funds' future lottery features. Our results show that MAX^{Hold} is a persistent, longer term, and significant predictor for funds' future lottery features, whereas the effect of MAX^{Fund} is short-term and loses its significance in the long-term.

Specifically, we estimate the following Fama-MacBeth cross-sectional regression:

$$MAX_{i,t+\tau}^{Fund} = \lambda_{0,t} + \lambda_{1,t} \cdot MAX_{i,t}^{Hold} + \lambda_{2,t} \cdot MAX_{i,t}^{Fund} + \sum_{k=1}^{K} \lambda_{k,t} \cdot Fund\ Controls_{k,t} + \varepsilon_{i,t+1}. \quad (3)$$

where the dependent variable is the fund's future maximum daily return from month $t+1$ to $t+12$ (i.e., $\tau = 1, 2, ..., 12$). $MAX_{i,t}^{Hold}$ is the lottery holdings of fund i in month t. $MAX_{i,t}^{Fund}$ is the fund maximum daily return in month t. Fund controls are the same as those in Table 3 including the alpha, the natural log of assets, natural log of age, expense ratio, turnover ratio, fund flows, TNA family, β^{SMB}, β^{HML}, β^{UMD}, return gap, active share, R^2, and fund volatility (VOL^{Fund}), all measured as of the end of previous month.

[Table 5 about here]

Table 5 presents the Fama-MacBeth cross-sectional regression coefficients on the lagged MAX^{Hold} and MAX^{Fund} while controlling for fund characteristics. Table 5 shows that funds' lottery holdings (MAX^{Hold}) significantly predict funds' future maximum daily returns for up to twelve months, whereas funds' maximum daily returns (MAX^{Fund}) exhibit only short-term

predictive power for up to four months. In other words, MAX^{Hold} has a strong and persistent predictive power for a fund's future lottery feature, while the effect of past MAX^{Fund} is only temporary. We plot the regression coefficients on MAX^{Hold} and MAX^{Fund}, respectively, in Figure 1, which clearly shows a decaying pattern for MAX^{Fund} but a persistent pattern for MAX^{Hold}. Overall, the results in Table 5, combined with those in Table 3, suggest that investors respond to lottery holdings of funds as they have strong predictive power for funds earning an extreme positive returns in the future.[20]

[Figure 1 about here]

4.4 Do fund managers themselves prefer lottery stocks? Evidence from managerial ownership

Previous section shows that flows respond positively to funds' lottery holdings especially for retail investors, which is consistent with funds catering to their investors' preferences for such stocks. However, it is also possible that fund managers themselves exhibit preference for such stocks. For example, Edelen, Ince, and Kadlec (2016) show that institutional investors have a strong tendency to buy stocks classified as overvalued (short leg of anomaly). A contrasting view is that institutional investors are more sophisticated, and therefore would try to avoid holding lottery stocks. In this section, we attempt to disentangle managers' and investors' lottery-type preferences. For this purpose, we use the ownership of portfolio managers in their own funds.[21] As shown in Ma and Tang (2017), managerial ownership can reduce the convexity of the option-like reward structures and weaken managers' agency-issue-induced incentives to take on more risk. We therefore expect that portfolio managers with greater

[20]Finally, Table A.6 of the Internet Appendix conducts bivariate portfolio sorts of fund lottery holdings (MAX^{Hold}) and fund daily maximum returns (MAX^{Fund}). The results show that MAX^{Hold} remains a strong and negative predictor even after controlling for MAX^{Fund} (spread between the extreme portfolios of MAX^{Hold} is -0.27 and significant at the 5% level). In contrast, MAX^{Fund} has little predictive power in predicting a fund's future performance after controlling for MAX^{Hold} (spread between the extreme portfolios of MAX^{Fund} is -0.11 and insignificant). These results suggest that MAX^{Hold} possesses information not contained in the fund daily maximum (MAX^{Fund}).

[21]We thank Linlin Ma and Yuehua Tang for sharing their managerial ownership data over the 2007–2014 period. For team-managed funds, we follow their methodology to construct the aggregate ownership of a team by adding up each manager's reported stake in the fund.

ownership stakes, ceteris paribus, engage in less risk-taking activities. In contrast, if fund managers exhibit a preference for lottery stocks, we would expect that funds with higher managerial ownership should hold more lottery stocks. To test these competing predictions, we estimate the following Fama-MacBeth regression:

$$Lottery\ Holdings_{i,t} = \alpha + \beta Ownership\ Rank_{i,t-1} + \gamma Fund\ Controls_{i,t-1} + \epsilon_t. \quad (4)$$

Since managerial ownership data is available on an annual basis, we conduct this analysis at the annual level. The dependent variable, *Lottery Holdings*, is the average fund lottery holdings measured by MAX^{Hold} or $MAX5^{Hold}$ of fund i in year t. Following Ma and Tang (2017), we use three measures of portfolio managerial ownership: *Ownership Dummy*, *Ownership Rank*, and *log*(\$*Ownership*). *Ownership Dummy* is an indicator variable that equals one if a portfolio manager has non-zero stake in a fund, and zero otherwise. *Ownership Rank* is a rank variable, which takes a value of one if managerial ownership is zero, and two to seven, if ownership falls in the range of \$1-\$10,000, \$10,001-\$50,000, \$50,001-\$100,000, \$100,001-\$500,000, \$500,001-\$1,000,000, and above \$1,000,000, respectively. *Log*(\$*Ownership*) is the natural logarithm of the dollar value of managerial ownership. Control variables are the same as in Eq. (1).

[Table 6 about here]

Table 6 presents the average intercept and slope coefficients from the Fama-MacBeth cross-sectional regressions. Model (1) shows that if portfolio managers have non-zero stakes in their funds, they are less likely to invest in lottery stocks. In models (2) and (3), we use *Ownership Rank* or *log*(*Ownership*) based on the dollar values of managerial ownership, and obtain similar evidence. We draw similar inferences from models (4) through (6), where the dependent variable is the $MAX5^{Hold}$. The coefficients on the three ownership measures are all significantly negative. Overall, results in Table 6 show that managers tend to avoid holding stocks with lottery features if their ownership is high in the funds. Together with our earlier finding of higher flows into funds with more lottery stocks, this evidence suggests that managers invest in lottery stocks to cater to their investors' preferences rather than their own

preference for such stocks.

4.5 Seasonality in lottery holdings

In the previous section, we show that managers tend to avoid lottery-like stocks when their ownership in the funds is high. In this section, we conduct seasonality tests in funds' tendency to invest in lottery stocks to test the possibility that funds invest in lottery stocks to engage in risk-shifting behavior, i.e., managers increase funds' risk towards the end of the year. Our empirical tests are predicated on two arguments. First, the literature on tournaments and the convex flow-performance relation (e.g., Brown, Harlow, and Starks, 1996; Chevalier and Ellison, 1997; Sirri and Tufano,1998; Huang, Wei, and Yan, 2007) suggests that many investors evaluate funds on a calendar-year basis, which may incentivize funds performing poorly earlier in the year to invest in lottery stocks towards the end of the year. Second, buying lottery stocks can be a way for the managers to increase their chances of winning by the end of the year and beating their peers. If this is true, we should expect seasonality in funds' holding of lottery stocks, with poorly performing managers increasing their positions in lottery stocks towards the end of the year.

For each quarter, we calculate changes in funds' lottery holdings by using share changes to capture active decisions by the portfolio managers rather than changes driven by stock prices (Schwarz, 2012). For each fund at quarter t and $t+1$, the lottery holdings' share changes are defined as,

$$\Delta MAX = \left(\sum_{i=1}^{N} MAX_{i,t} \cdot w_{i,t+1}\right) - \left(\sum_{i=1}^{N} MAX_{i,t} \cdot w_{i,t}\right) \tag{5}$$

where i represents stock i in a fund's portfolio. $w_{i,t+1} = (p_{i,t} \cdot Shares_{i,t+1})/(\sum_{i=1}^{N} p_{i,t} \cdot Shares_{i,t+1})$ is the hypothetical portfolio weight in stock i in quarter $t+1$ based on the price at the end of quarter t, $p_{i,t}$. $w_{i,t} = (p_{i,t} \cdot Shares_{i,t})/(\sum_{i=1}^{N} p_{i,t} \cdot Shares_{i,t})$ is the actual portfolio weight in stock i in quarter t, again based on the price $p_{i,t}$.

To examine seasonality in lottery holdings, Figure 2 presents the changes in shares of

lottery stocks (ΔMAX) held by the funds between the second quarter and the first quarter (Panel A), between the third quarter and the first two quarters (Panel B), and between the fourth quarter and the first three quarters (Panel C). To the extent that the risk-shifting behavior is likely to occur more towards the end of the year, Panel A serves as a placebo test for seasonality in lottery holdings. In Panel A, we sort funds into quintiles at the beginning of the second calendar quarter based on funds' performance in the first quarter of year t. *Worst Perf* represents the bottom 20% of funds with the worst performance (Quintile 1) and *Best Perf* represents the top 20% of funds with the best performance (Quintile 5). Panel A shows that there is no sharp distinction between lottery holdings in the second quarter for funds with poor or good performance. However, results look significantly different when we examine lottery holdings for the next two quarters (i.e., the second half of the year). In Panel B, we sort funds into quintiles at the beginning of the third calendar quarter based on funds' performance in the first half of year t. Panel B shows that funds with poor performance in the first half of the year significantly increase their lottery holdings in the third calendar quarter, relative to funds with good performance. Relation between the increase in lottery holdings and past fund performance decreases monotonically from funds with the worst performance to funds with the best performance. We observe similar patterns for the fourth quarter when we sort funds based on their performance in the first three quarters of the year. Funds with the worst performance in the first three quarters increase their lottery holdings the most during the last calendar quarter.

[Figure 2 about here]

We conduct regression analyses to more formally verify seasonality in lottery holdings. Table 7 reports the average slope coefficients and R-squares from the Fama and MacBeth (1973) cross-sectional regressions using funds' changes in shares of lottery stocks (ΔMAX) as the dependent variable, which captures active decisions by portfolio managers. We estimate the regression separately for each of the three calendar quarters starting from the second quarter of the year. We use two measures for funds' relative performance: adjusted return (*adj.ret*) and *returnrank*. *Adj.ret* is the difference between a fund's performance and the

median fund performance, where we proxy fund performance by the quarterly alpha estimated using fund's daily returns within a quarter and the Carhart 4-factor model. *Returnrank* is the percentile return rank of a fund. We measure both *Adj.ret* and *returnrank* up to the beginning quarter of the dependent variable.[22]

[Table 7 about here]

First two columns of Table 7 report the results for the second calendar quarter. Results show that past relative performance, as measured by *adj.ret* and *returnrank* in the first quarter, does not predict changes in shares of lottery stocks in the next quarter. The coefficients on *adj.ret* and *returnrank* are statistically insignificant. However, moving to the third quarter, models (3) and (4) show that past relative performance during the first and second quarter is negatively related to changes in lottery holdings. The coefficients on *adj.ret* and *returnrank* are -0.003 (t-stat. $= -3.02$) and -0.003 (t-stat. $= -2.30$), respectively, indicating that funds with poor performance in the first two quarters are more likely to increase their lottery holdings during the third quarter than funds with good performance. Similarly, models (5) and (6) show that funds performing poorly in the first three quarters of the year increase their lottery holdings in the last quarter (i.e., at the end of the calendar year). The coefficients on *adj.ret* and *returnrank* are significantly negative: -0.006 (t-stat. $= -3.64$) and -0.003 (t-stat. $= -3.47$), respectively. Overall, Table 7 provides evidence consistent with the tournament behavior in mutual funds where managers with poor performance earlier in the year tend to increase their positions in lottery stocks to try and beat their peers by the end of the year.

5 Asset Pricing Implications of Lottery Stock Holdings

In this section, we explore the asset pricing implications of mutual funds holding lottery stocks. Flows to mutual funds have been shown to create distortions in capital allocation

[22]For example, if the dependent variable is ΔMAX in the second quarter of year t, we use *adj.ret* and *returnrank* in the first quarter of the same year. If the dependent variable is the ΔMAX in the third (fourth) quarter of year t, we use the average *adj.ret* and *returnrank* over the first two (three) quarters.

across stocks as managers usually increase positions in existing stock holdings thus create price pressure associated with these stocks (Coval and Stafford, 2007; Akbas et al., 2015). Motivated by these findings, we hypothesize that if mutual funds disproportionately purchase lottery stocks that are already overvalued, and if the resulting price pressure further exacerbates these stocks' overvaluation, we would expect these stocks to experience a price reversal following higher aggregate lottery holdings by mutual funds. Our results support this prediction.

5.1 Research design

We use the lottery demand factor return in Bali et al. (2017) in our main test, which captures the returns associated with lottery demand.[23] We use predictive regression where the dependent variable is the one-quarter-ahead lottery demand factor (FMAX) constructed by Bali et al. (2017) and the key independent variable is lagged aggregate lottery holdings of mutual funds. The empirical prediction is that, to the extent that mutual fund holdings' of lottery stocks (i.e., lottery demand) exacerbates the overpricing of lottery stocks, higher lottery holdings should imply more pronounced underperformance of lottery stocks, thus a more negative FMAX factor return.

We construct an aggregate measure of lottery holdings of mutual funds by taking the average lottery holding of all mutual funds. Three proxies for lottery holdings are MAX^{Hold}, MAXProp, and Top 10 MAX^{Hold}, all of which are defined in Section 3. We then run predictive regression of the lottery demand factor on lagged aggregate lottery holdings ($\text{LTY}^{Holding}$),

$$FMAX_t = a + b \cdot LTY_{t-1}^{Holding} + u_t \tag{6}$$

where $FMAX_t$ is the lottery demand factor return in quarter t. $\text{LTY}^{Holding}$ is the aggregate lottery holdings of mutual funds. Second, we also control for the contemporaneous returns

[23]Specifically, Bali et al. (2017) form the lottery-demand factor, denoted FMAX, using the factor-forming technique pioneered by Fama and French (1993). The FMAX factor return in month $t+1$ is taken to be the average return of the 2 value-weighted high-MAX (i.e., the maximum daily return, a proxy for lottery feature of individual stock) portfolios minus the average return of the 2 value-weighted low-MAX portfolios, where the 6 portfolios are generated by the intersections of the 2 market capitalization-based groups and the 3 MAX groups from independent sorts based on NYSE breakpoints and an ascending sort of stock MAX.

on the three Fama and French factors (MKT, SMB, and HML), a momentum factor (UMD), and the Pastor-Stambaugh liquidity factor (LIQ) to investigate the ability of lottery holdings to predict benchmark-adjusted returns,

$$FMAX_{i,t} = a + b \cdot LTY_{t-1}^{Holding} + cMKT_t + dSMB_t + eHML_t + fUMD_t + gLIQ_t + u_t \quad (7)$$

Panel A of Table 8 reports univariate regression results of lottery demand factor return on lagged aggregate lottery holdings of mutual funds. First, the coefficients on aggregate lottery holdings are all negative and statistically significant, indicating that the FMAX factor return is more negative when fund lottery holdings are high. This implies that fund lottery holdings, in the aggregate, exacerbate mispricing in the cross-section of lottery stocks. Our hypothesis is also supported in the multivariate regression in Panel B when controlling for the lagged FMAX factor return, as well as the contemporaneous Fama-French-Carhart four factors plus the liquidity risk factor of Pastor and Stambaugh (2003). Regardless of the proxies for aggregate lottery holdings, the coefficients are always negative and significant, suggesting a more pronounced subsequent underperformance of lottery stocks when lottery holdings are higher. Overall, the results in Table 8 suggest that aggregate mutual fund lottery holdings exacerbate the lottery premium. In other words, mutual fund holdings of lottery stocks contribute to the cross-sectional mispricing through the purchase of overvalued lottery stocks.

[Table 8 about here]

6 Conclusion

It is a commonly-held belief that lottery stocks are held by individual investors. This study shows that even some institutional investors, such as mutual funds, hold these stocks. We document large cross-sectional differences in lottery holdings among actively managed U.S. equity funds. We examine the economic incentives behind some actively managed mutual funds to favor lottery stocks, and its implications for both fund managers and fund investors.

We show that certain fund characteristics are related to funds' tendency to hold lottery stocks. Specifically, funds with high lottery holdings are smaller in size, younger, and have poor past performance – characteristics typically associated with funds' incentives to attract greater investor flows. We also show that the lottery holdings of funds help attract flows, especially from retail investors. Employing a difference-in-differences approach, we find that funds with more lottery stocks attract significantly more flows compared to their peers only after the filing dates, and there is no difference between the average daily flow for the treatment and control groups through the pre-disclosure periods. Taken together, our findings uncover new evidence of funds gathering assets by catering to investor preferences, even though investors suffer from worse future fund performance.

We further disentangle the lottery-type preferences of fund managers from those of their investors by investigating the relation between portfolio managers' ownership and lottery holdings. We find that managers with high ownership tend to avoid stocks with lottery-like features. This evidence is consistent with managers catering to investors' preferences for lottery stocks rather than their own preference for such stocks. In addition, we document strong seasonality as managers performing poorly earlier in the year significantly increase their lottery holdings towards the end of the year. This finding is consistent with the agency problems in mutual funds where managers engage in risk-shifting behavior to increase their risk through greater investments in lottery stocks towards the end of the year if they lag behind their peers earlier in the year.

Finally, we explore the asset pricing implications of mutual funds holding lottery stocks. We show that higher aggregate mutual fund lottery holdings imply a more negative lottery demand factor return and exacerbate the overpricing of lottery stocks in the cross-section, which complements previous studies on flows to mutual funds creating distortions in capital allocation across stocks.

Overall, our paper provides novel evidence of individual investors obtaining exposure to lottery stocks through their investments in mutual funds, and fund managers taking advantage of such preferences to garner more flows into their funds and engage in risk-shifting behavior.

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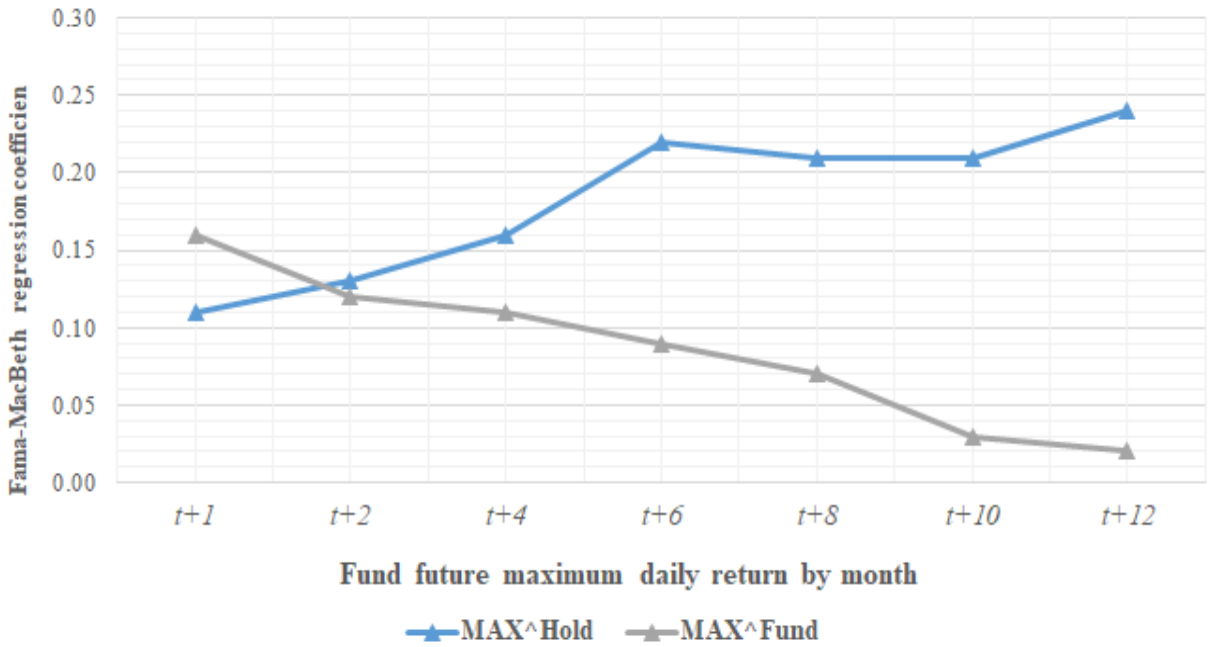
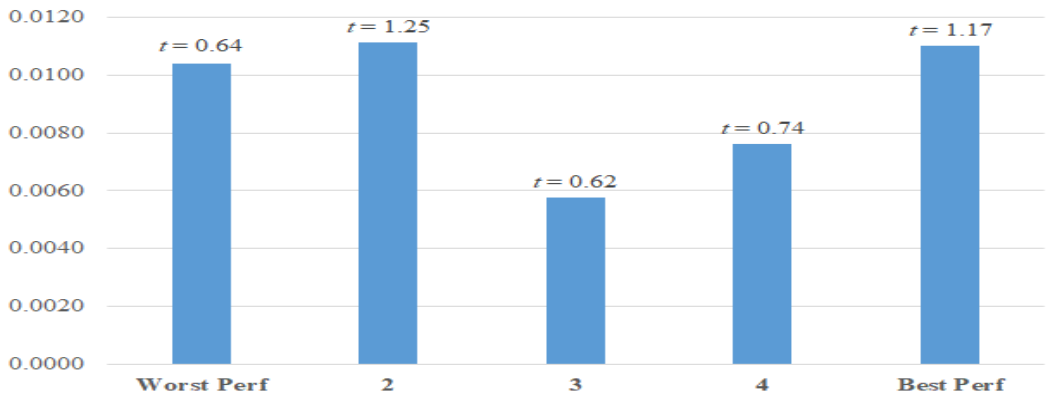
Figure 1: How long does MAX^{Hold} or MAX^{Fund} persist as a predictor of future fund maximum daily returns?



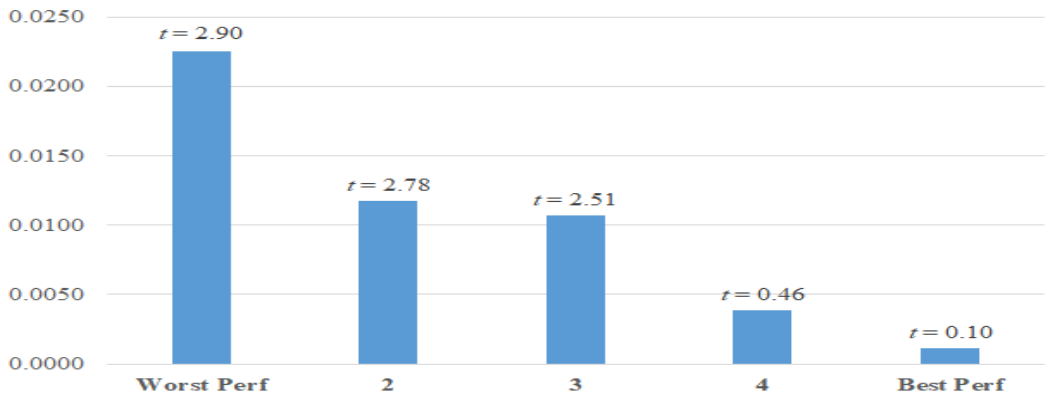
This figure shows the Fama-MacBeth cross-sectional regression coefficients on the lagged MAX^{Hold} (the blue solid line) and MAX^{Fund} (the gray solid line) in month t. The dependent variable is the future fund maximum daily returns (MAX^{Fund}) from month $t+1$ to $t+12$, as a measure of fund lottery feature in the future. MAX^{Hold} is the holding-weighted lottery characteristics using stock maximum daily returns within the current month, based on a fund's most recent portfolio holdings. MAX^{Fund} is the maximum daily fund return within a month. All regressions include fund controls in Table 3 such as the alpha, the natural log of assets, natural log of age, expense ratio, turnover ratio, fund flows, TNA family, β^{SMB}, β^{HML}, β^{UMD}, return gap, active share, R^2, and fund volatility (VOL^{Fund}), all measured as of the end of previous month.

Figure 2: Seasonality in lottery holdings

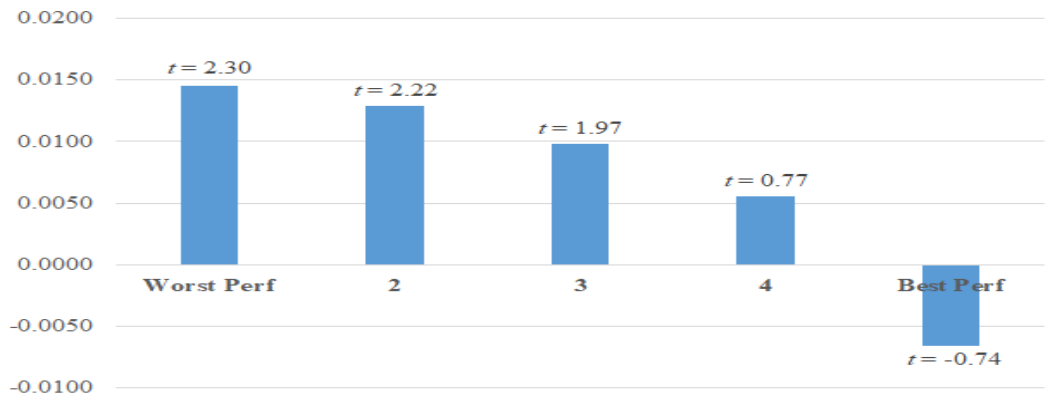
Panel A: Average changes in shares of lottery stocks (ΔMAX) in the 2nd quarter



Panel B: Average changes in shares of lottery stocks (ΔMAX) in the 3rd quarter



Panel C: Average changes in shares of lottery stocks (ΔMAX) in the 4th quarter



This figure presents the changes in shares of lottery stocks (ΔMAX) held by the funds between the 2nd quarter and the first quarter (Panel A), between the 3rd quarter and the first two quarters (Panel B), and between the 4th quarter and the first three quarters (Panel C). Panel A sorts funds into quintiles at the beginning of the 2nd calendar quarter based on the fund performance in the first quarter of year t. *Worst Perf* represents the bottom 20% of funds (Quintile 1) with the worst performance and *Best Perf* represents the top 20% of funds (Quintile 5) with the best performance. Panel B sorts funds into quintiles at the beginning of the 3rd calendar quarter based on the fund performance in the first half of year t. Panel C sorts funds into quintiles at the beginning of the 4th calendar quarter based on the fund performance in the first three quarters of year t. t-statistics are estimated based on the time-series of changes in lottery stocks held by funds in each quintile.

Table 1: Descriptive summary statistics and correlation coefficients

This table reports the summary statistics and correlation coefficients of the key variables used in the empirical analysis. Our sample includes 115,655 fund-quarter observations for 3,066 funds between January 2000 and December 2014. MAX^{Hold} is the holding-weighted lottery characteristics using stock maximum daily returns within the current month, based on a fund's most recent portfolio holdings. $MAX5^{Hold}$ is the holding-weighted lottery characteristics using the average of the five highest stock daily returns within the current month, based on a fund's most recent portfolio holdings. Alpha is the quarterly percentage alpha calculated from the Fama-French-Carhart four-factor model using fund daily returns. TNA ($ million) is the total net assets under management at the end of the quarter. Age is the fund age based on the oldest share class in the fund. Expense is the annual expense ratio. Turnover is the annual turnover ratio as reported in the CRSP survivorship bias free mutual fund database. Flow is the dollar fund flows over a quarter scaled by beginning-of-the-quarter TNA.

Variable	N	Mean	Median	Q1	Q3
Panel A: Quarterly lottery holding measures (%)					
MAX^{Hold}	97,673	4.58	3.93	3.05	5.32
$MAX5^{Hold}$	97,671	2.77	2.38	1.86	3.16
Panel B: Other variables					
Quarterly alpha (%)	115,655	-0.49	-0.31	-1.89	1.16
TNA ($ million)	115,655	1,278.52	296.80	95.70	995.00
Age (year)	115,655	14.77	11.42	6.75	18.00
Expense (%)	114,783	1.24	1.20	0.98	1.49
Turnover (%)	115,187	86.20	63.00	33.00	108.00
Flow (%)	114,987	1.89	-1.30	-4.39	3.02

Panel C: Correlations

	MAX^{Hold}	$MAX5^{Hold}$	Alpha	TNA	Age	Expense	Turnover	Flow
MAX^{Hold}	1							
$MAX5^{Hold}$	0.89	1						
Alpha	-0.11	-0.12	1					
TNA	-0.10	-0.10	0.03	1				
Age	-0.18	-0.18	0.00	0.40	1			
Expense	0.16	0.15	-0.02	-0.31	-0.17	1		
Turnover	0.23	0.23	-0.05	-0.16	-0.10	0.22	1	
Flow	0.01	0.01	0.15	0.04	-0.20	-0.05	-0.08	1

Table 2: Fund characteristics by lottery holdings

This table shows the average characteristics of portfolios of mutual funds in the portfolio formation quarter. At the beginning of each calendar quarter, we form decile portfolios of mutual funds based on their lottery holdings. Decile 1 contains funds with the lowest lottery holdings and decile 10 contains funds with the highest lottery holdings. We also present results for the fifth lottery holdings decile. Panel A shows the fund characteristics. Fund lottery holdings in this table is measured by MAX^{Hold}, the holding-weighted lottery characteristics using stock maximum daily returns within the current month. Other variables are defined in Table 1. Panel B shows the factor exposures and fund alpha, all based on the Fama-French-Carhart four-factor using fund daily returns during the portfolio formation quarter. Panel C shows holding-weighted stock characteristics including size, book-to-market (BM), and past six-month cumulative stock returns over the period from month $t-7$ to $t-2$ (MOM). Panel D shows the heterogeneity of lottery holdings within different investment style. The corresponding t-statistic to test the difference in means is provided for each characteristic.

Panel A: Fund characteristics

Portfolio	MAX^{Hold}	Assets (millions)	Age (year)	Expense ratio (%)	Turnover
Low MAX^{Hold}	3.16	1841.43	18.11	1.16	0.62
5	4.17	1805.11	15.99	1.21	0.84
High MAX^{Hold}	7.08	667.64	12.55	1.41	1.18
Difference	3.92	-1173.79	-5.56	0.26	0.57
t-stat	11.46	-12.72	-22.62	21.93	13.38

Panel B: Fund factor exposures and alpha

	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	Alpha (%)
Low MAX^{Hold}	0.89	-0.07	0.11	-0.02	-0.14
5	0.96	0.07	0.00	0.03	-0.44
High MAX^{Hold}	0.96	0.67	-0.01	0.05	-1.02
Difference	0.07	0.74	-0.12	0.07	-0.88
t-stat	4.51	29.35	-3.03	2.39	-2.07

Table 2. (Continued)

Panel C: Holding-weighted stock characteristics

	Size	BM	MOM
Low MAX^{Hold}	10.32	0.38	7.39
5	9.70	0.34	9.79
High MAX^{Hold}	7.29	0.33	19.66
Difference	-3.03	-0.05	12.27
t-stat	-20.33	-2.33	3.11

Panel D: Lottery holdings across different investment styles

	Mid-cap	Small-cap	Micro-cap	Growth	Growth and Income
Low MAX^{Hold}	3.68	4.24	5.17	3.26	3.20
5	4.74	5.48	6.76	4.00	3.77
High MAX^{Hold}	6.70	7.62	9.39	6.20	5.27
Difference	3.02	3.39	4.21	2.94	2.07
t-stat	9.18	9.35	11.07	11.67	11.35

Table 3: Fund lottery holdings and fund flows

This table reports the results of panel regressions from the model:

$$\begin{aligned} Flow_{i,t+1} &= \lambda_0 + \lambda_1 \cdot Lottery\ Holdings_{i,t} + \lambda_2 \cdot Low_{i,t} + \lambda_3 \cdot Mid_{i,t} + \lambda_4 \cdot High_{i,t} \\ &\quad + \sum_{k=1}^{K} \lambda_k \cdot Fund\ Controls_{k,t} + \epsilon_{i,t+1}. \end{aligned}$$

The dependent variable is the quarterly percentage net flow during the lead quarter. Three proxies for lottery holdings are MAX^{Hold}, MAXProp, and Top 10 MAX^{Hold}. MAX^{Hold} is the average monthly MAX^{Hold} during a quarter. MAXProp is average monthly proportion of fund's assets that is invested in lottery stocks (i.e., stocks whose MAX is in the top quintile among all stocks) during a quarter. Top 10 MAX^{Hold} is the average monthly holding-weighted lottery measure (i.e., MAX of the stocks) for the top 10 stocks held by the funds based on their investments during a quarter. Low perf, Mid perf, and High perf are the bottom 20%, middle 60%, and top 20% performance quintiles for a fund in quarter t as defined in Sirri and Tufano (1998). Other fund controls include fund maximum daily return (MAX^{Fund}), the natural log of assets, natural log of age, expense ratio, turnover ratio, natural log of TNA family, and flows across all funds in a given style (style flow), all measured as of the end of quarter t. LoserProp (WinnerProp) is the proportion of the fund's assets invested in the first (fifth) quintile of stocks sorted in ascending order according to their returns over the past three months. The model is estimated with time and fund fixed effects and their corresponding t-statistics with standard errors clustered at the fund level. Panel B reports the results separately for funds with retail or institutional clientile. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Dependent variable = Flows during quarter $t+1$

Variables	(1)	(2)	(3)
MAX^{Hold}	0.652***		
	(3.30)		
MAXProp		0.237***	
		(2.62)	
Top 10 MAX^{Hold}			0.430***
			(3.71)
MAX^{Fund}	-0.013	0.122	0.076
	(-0.07)	(0.73)	(0.45)
Low perf	9.565***	9.500***	9.547***
	(7.74)	(7.70)	(7.73)
Mid perf	0.949***	0.967***	0.940***
	(3.89)	(3.95)	(3.86)
High Perf	11.558***	11.673***	11.584***
	(8.79)	(8.90)	(8.82)
log(TNA)	-2.603***	-2.601***	-2.594***
	(-10.06)	(-10.04)	(-10.02)
log(Age)	-5.030***	-5.051***	-5.036***
	(-14.10)	(-14.18)	(-14.13)
Expense	0.983***	0.987***	0.985***
	(3.30)	(3.32)	(3.31)
Turnover	-0.163	-0.149	-0.155
	(-0.67)	(-0.61)	(-0.63)
TNA family	1.107**	1.112**	1.108**
	(2.41)	(2.42)	(2.41)
Style flow	0.560***	0.573***	0.570***
	(4.51)	(4.59)	(4.57)
LoserProp	-0.332***	-0.320***	-0.312***
	(-4.39)	(-4.28)	(-4.15)
WinnerProp	1.635***	1.631***	1.641***
	(17.01)	(17.04)	(17.04)
Constant	-2.748***	-1.899***	-2.513***
	(-3.94)	(-2.83)	(-3.70)
Fund/Time fixed effects	Y/Y	Y/Y	Y/Y
Observations	65,369	65,369	65,369
R-squared	0.093	0.090	0.095

Table 3. (Continued)

Panel B: Flows for funds with retail versus institutional clientile

	(1)	(2)	(3)	(4)	(5)	(6)
	Retail funds			Institutional funds		
MAX^{Hold}	0.830***			0.608**		
	(2.76)			(2.36)		
MAXProp		0.453**			0.247**	
		(2.69)			(1.98)	
Top 10 MAX^{Hold}			0.368***			0.246**
			(2.81)			(2.76)
Diff. in coef. (Retail − Inst.)	0.222***	0.206**	0.122**			
p-value	0.00	0.03	0.05			
Fund controls	Y	Y	Y	Y	Y	Y
Fund/Time fixed effects	Y/Y	Y/Y	Y/Y	Y/Y	Y/Y	Y/Y
Observations	31,049	31,049	31,049	34,320	34,320	34,320
R-squared	0.111	0.111	0.111	0.078	0.078	0.078

Table 4: Daily and monthly flow responses to funds' holdings disclosure

Panel A of the table reports the results of difference-in-differences (DID) analysis of the following regression:

$$flow_{i,t} = \beta_0 + \beta_1 \times I(treat_{i,t}) + \beta_2 \times I(post_{i,t}) + \beta_3 \times I(treat)_{i,t} \times I(post_{i,t}) + \epsilon_{it}$$

The dependent variable is the daily percentage flow from TrimTabs, defined as the ratio of dollar flows to prior day's total net assets. $I(treat)$ is a dummy variable equal to one if the fund has the highest lottery holdings ranked among the top 20% of funds and zero if the fund has the lowest lottery holdings ranked among the bottom 20% of funds, observed six weeks before ($I(post) = 0$) and six weeks after ($I(post) = 1$) the filing dates on which funds disclose their portfolio holdings. Here β_3 is the parameter of interest (i.e., the DID estimator). We use a six-week period around the filing date to evenly split the period between two consecutive quarterly disclosures. Panel B repeats similar analyses using monthly flows from the CRSP Survivorship Bias Free Mutual Fund Database that has the comprehensive coverage of funds. The standard errors are clustered at the fund level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Daily flow responses to funds' portfolio disclosure based on the TrimTabs dataset

β_1: I(treat)	0.002 (0.20)	Avg. daily flow of treatment group in pre-treatment period less avg. daily flow of control group in pre-treatment period
β_2: I(post)	0.001 (0.75)	Avg daily flow of control group in post-treatment period less avg. daily flow of control group in pre-treatment period
β_3: $I(treat) \times I(Post)$	0.125*** (6.28)	the DID estimator
β_0: Intercept	0.032*** (24.25)	Avg. daily flow of control group in the pre-treatment period
Adjusted R^2	0.232	

Panel B: Monthly flow responses to funds' portfolio disclosure based on the CRSP sample

β_1: I(treat)	0.015 (0.43)	Avg. monthly flow of treatment group in pre-treatment period less avg. monthly flow of control group in pre-treatment period
β_2: I(post)	0.007 (1.02)	Avg monthly flow of control group in post-treatment period less avg. monthly flow of control group in pre-treatment period
β_3: $I(treat) \times I(Post)$	0.180*** (5.25)	the DID estimator
β_0: Intercept	0.124*** (12.05)	Avg. monthly flow of control group in the pre-treatment period
Adjusted R^2	0.350	

Table 5: How long does MAX^{Hold} or MAX^{Fund} persist as a predictor of future fund maximum daily returns?

The table shows the Fama-MacBeth cross-sectional regression coefficients on the lagged MAX^{Hold} and MAX^{Fund} in month t.

$$MAX^{Fund}_{i,t+\tau} = \lambda_{0,t} + \lambda_{1,t} \cdot MAX^{Hold}_{i,t} + \lambda_{2,t} \cdot MAX^{Fund}_{i,t} + \sum_{k=1}^{K} \lambda_{k,t} \cdot Fund\ Controls_{k,t} + \varepsilon_{i,t+1}.$$

The dependent variable is the future fund maximum daily returns (MAX^{Fund}) from month $t+1$ to $t+12$, as a measure of fund lottery feature in the future. MAX^{Hold} is the holding-weighted lottery characteristics using stock maximum daily returns within the current month, based on a fund's most recent portfolio holdings. MAX^{Fund} is the maximum daily fund return within a month. All regressions include fund controls in Table 3 such as the alpha, the natural log of assets, natural log of age, expense ratio, turnover ratio, fund flows, TNA family, β^{SMB}, β^{HML}, β^{UMD}, return gap, active share, R^2, and fund volatility (VOL^{Fund}), all measured as of the end of previous month. All right-hand variables are z-scored (demeaned and divided by their standard deviation) within each quarter. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Coef.	MAX$^{Fund}_{t+1}$	MAX$^{Fund}_{t+2}$	MAX$^{Fund}_{t+3}$	MAX$^{Fund}_{t+4}$	MAX$^{Fund}_{t+5}$	MAX$^{Fund}_{t+6}$
MAX$^{Hold}_{t}$	0.11***	0.13***	0.13***	0.16***	0.17***	0.22***
	(4.34)	(4.75)	(4.38)	(4.90)	(4.72)	(4.45)
MAX$^{Fund}_{t}$	0.16***	0.15**	0.12**	0.11*	0.09	0.09
	(2.94)	(2.62)	(2.36)	(1.95)	(1.27)	(1.25)
Fund controls	Y	Y	Y	Y	Y	Y
R-squared	0.63	0.62	0.61	0.60	0.59	0.57

Coef.	MAX$^{Fund}_{t+7}$	MAX$^{Fund}_{t+8}$	MAX$^{Fund}_{t+9}$	MAX$^{Fund}_{t+10}$	MAX$^{Fund}_{t+11}$	MAX$^{Fund}_{t+12}$
MAX$^{Hold}_{t}$	0.31***	0.21***	0.19***	0.21***	0.31***	0.24***
	(2.78)	(5.19)	(4.88)	(5.24)	(2.78)	(5.49)
MAX$^{Fund}_{t}$	0.08	0.07	0.05	0.03	0.03	0.02
	(1.01)	(0.76)	(0.54)	(0.35)	(0.33)	(0.21)
Fund controls	Y	Y	Y	Y	Y	Y
R-squared	0.56	0.56	0.55	0.54	0.53	0.52

Table 6: Fund lottery holdings and portfolio manager ownership

The table reports the average slope coefficients and R-squares from the Fama and MacBeth (1973) cross-sectional regressions. In Panel A, the dependent variable is the average lottery holdings measured by MAX^{Hold} in year $t+1$. In Panel B, the dependent variable is the average lottery holdings measured by MAX5^{Hold} in year $t+1$. The variable *Ownership Dummy* is an indicator variable that equals one if a portfolio manager has non-zero stake in a fund and zero otherwise. The variable *Ownership Rank* is a rank variable, which is set to one if \$Ownership is \$0, and two, three, four, five, six, and seven, if it falls in the range of \$1-\$10,000, \$10,001-\$50,000, \$50,001-\$100,000, \$100,001-\$500,000, \$500,001-\$1,000,000, and above \$1,000,000, respectively. *Log(\$Ownership)* is the log dollar amount of portfolio manager ownership. All three ownership proxies are measured as of the end of year t. *Past year performance* is the average quarterly alpha of the fund in year t. Fund controls include the lagged natural log of assets, natural log of age, expense ratio, turnover ratio, and TNA family, all measured as of the end of year t. Fund flow is the net flow in year t. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 2007 – 2014 due to availability of the ownership data.

	Dep var. = MAX^{Hold}_{t+1}			Dep var. = MAX5^{Hold}_{t+1}		
	(1)	(2)	(3)	(4)	(5)	(6)
Ownership dummy$_t$	-0.162**			-0.095***		
	(-2.64)			(-2.89)		
Ownership rank$_t$		-0.036***			-0.024**	
		(-2.75)			(-2.73)	
Log(\$Ownership)$_t$			-0.012**			-0.008**
			(-2.65)			(-2.84)
Past year perf$_t$	-0.132	-0.137	-0.134	-0.131	-0.136	-0.132
	(-1.58)	(-1.66)	(-1.60)	(-1.56)	(-1.63)	(-1.58)
log(TNA)$_t$	-0.234**	-0.233**	-0.234**	-0.233**	-0.232**	-0.233**
	(-2.43)	(-2.43)	(-2.43)	(-2.42)	(-2.42)	(-2.42)
log(Age)$_t$	0.019	0.014	0.016	0.018	0.014	0.016
	(1.03)	(0.90)	(0.97)	(1.03)	(0.90)	(0.97)
Expense$_t$	1.004*	0.987	0.997*	1.007*	0.989	1.000*
	(1.74)	(1.70)	(1.73)	(1.74)	(1.71)	(1.73)
Turnover$_t$	0.169**	0.164**	0.169*	0.171*	0.166*	0.170*
	(2.16)	(2.29)	(1.95)	(1.98)	(1.93)	(1.97)
Flow$_t$	-0.192	-0.195	-0.193	-0.192	-0.195	-0.193
	(-1.52)	(-1.56)	(-1.54)	(-1.52)	(-1.56)	(-1.54)
TNA Family$_t$	0.012	0.007	0.011	0.012	0.007	0.011
	(1.51)	(1.57)	(1.52)	(1.48)	(1.53)	(1.49)
Observations	9,938	9,938	9,938	9,938	9,938	9,938
Adj. R^2	0.10	0.10	0.09	0.10	0.10	0.09

Table 7: Seasonality in lottery holdings

The table reports the average slope coefficients and R-squares from the Fama and MacBeth (1973) cross-sectional regressions using funds' lottery holding share changes (ΔMAX) as the dependent variable, which captures active decisions by the portfolio managers. *Adj. ret* is the difference between a fund's performance and the median fund performance, where performance is measured by the quarterly alpha estimated using fund daily returns within a quarter based on the Carhart 4-factor model. *Return rank* is the percentile performance rank of the fund. To control for mean-reversion in lottery holdings, we include the average holding-weighted lottery characteristics (MAX^{Hold}) from the first quarter up to the beginning of quarter when the dependent variable is measured. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Dep var. = ΔMAX in the 2nd qtr.		Dep var. = ΔMAX in the 3rd qtr.		Dep var. = ΔMAX in the 4th qtr.	
	(1)	(2)	(3)	(4)	(5)	(6)
Adj.ret in the 1st qtr.	-0.001					
	(-0.34)					
Return rank in the 1st qtr.		0.002				
		(0.60)				
Avg. Adj.ret (1st + 2nd)			-0.003***			
			(-3.02)			
Avg. return rank (1st + 2nd)				-0.003**		
				(-2.30)		
Avg. Adj.ret (1st + 2nd + 3rd)					-0.006***	
					(-3.64)	
Avg. return rank (1st + 2nd +3rd)						-0.003***
						(-3.47)
MAX^{Hold} in the 1st qtr.	-0.006	-0.005				
	(-1.45)	(-1.29)				
Avg. MAX^{Hold} (1st + 2nd)			-0.010	-0.009		
			(-1.15)	(-1.00)		
Avg. MAX^{Hold} (1st + 2nd + 3rd)					-0.011	-0.012
					(-1.21)	(-1.16)
Observations	23,806	23,806	23,408	23,408	23,098	23,098
Adj. R^2	0.01	0.01	0.01	0.01	0.01	0.01

Table 8: Lottery holdings and the lottery factor premium

The table reports predictive regressions of the lottery factor premium on lottery holdings. The dependent variable is the one-quarter-ahead lottery factor premium (FMAX) in Bali, Brown, Murray, and Tang (2017), defined as the value-weighted average return of the high-MAX portfolios minus the average return of the low-MAX portfolios. The FMAX factor portfolio is designed to capture returns associated with lottery demand while maintaining neutrality to market capitalization. A more negative FMAX factor return corresponds to stronger lottery demand thus more underperformance of lottery stocks. The main independent variable is the aggregate fund lottery holdings at the end of quarter t, defined as the average lottery holdings of all mutual funds. Three proxies for lottery holdings are MAX^{Hold}, MAXProp, and Top 10 MAX^{Hold}. MAX^{Hold} is the average monthly MAX^{Hold} during a quarter. MAXProp is average monthly proportion of fund's assets that is invested in lottery stocks (i.e., stocks whose MAX is in the top quintile among all stocks) during a quarter. Top 10 MAX^{Hold} is the average monthly holding-weighted lottery measure (i.e., MAX of the stocks) for the top 10 stocks held by the funds based on their investments during a quarter. Panel A reports the univariate regressions where the only independent variable is the lottery holding. Panel B reports the multivariate regressions controlling for the lagged FMAX factor as well as the contemporaneous Fama-French-Carhart four factors plus the liquidity risk factor (ILLIQ) of Pastor and Stambaugh (2013). Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate significance of the lottery holding coefficient at the 10%, 5%, and 1% level, respectively.

Panel A: Univariate regression, Dep. Var = FMAX

	MAX^{Hold}	MAXProp	Top 10 MAX^{Hold}
Coef.	-0.65***	-0.50***	-0.74**
t-stat	(-2.78)	(-3.27)	(-2.70)
Adj. R^2 (%)	6.29	5.84	7.88

Panel B: Multivariate regression, Dep. Var = FMAX

	MAX^{Hold}	MKTRF	SMB	HML	UMD	LIQ	Lag FMAX
Coef.	-0.77***	0.62	0.83	-0.34	0.04	-4.85	0.03
t-stat	(-4.11)	(5.85)	(7.82)	(-1.99)	(0.44)	(-0.93)	(0.43)
Adj. R^2 (%)	78.84						
	MAXProp	MKTRF	SMB	HML	UMD	LIQ	Lag FMAX
Coef.	-0.81***	0.60	0.72	-0.65	0.02	1.19	0.06
t-stat	(-3.54)	(7.36)	(7.06)	(-3.95)	(0.26)	(0.26)	(0.62)
Adj. R^2 (%) (%)	79.29						
	Top 10 MAX^{Hold}	MKTRF	SMB	HML	UMD	LIQ	Lag FMAX
Coef.	-0.90***	0.63	0.83	-0.34	0.05	-5.07	0.05
t-stat	(-3.90)	(5.75)	(7.94)	(-1.96)	(0.48)	(-0.95)	(0.64)
Adj. R^2 (%)	80.74						

Why Do Mutual Funds Hold Lottery Stocks?

Internet Appendix

This appendix consists of three parts. Section A.1 investigates the predictive power of fund lottery holdings on future fund performance. We first perform a univariate portfolio-level analysis of lottery holdings and its relation to future fund performance. We then conduct multivariate cross-sectional regressions, and show that funds with more lottery holdings significantly underperform in the future and this result is robust after controlling for a large number of fund characteristics and other predictors of fund performance. Section A.2 conducts a battery of robustness checks to examine the relation between lottery holdings and future average fund returns. Section A.3 conducts bivariate portfolio-level analyses after controlling for other known predictors of fund performance.

A.1 Lottery Holdings and Future Fund Performance

A.1.1 Univariate sorts

Table A.2 presents the univariate portfolio results. At the beginning of each calendar quarter, we sort funds into deciles based on their lottery holdings (MAX^{Hold} or $MAX5^{Hold}$). Decile 1 contains funds with the lowest lottery holdings and decile 10 contains funds with the highest lottery holdings. We then examine the performance of the funds in different deciles during the following quarter. Each portfolio is equally-weighted and has the same number of funds at the start of each quarter. A fund remains in the same portfolio for the next three months.

[Table A.2 about here]

Table A.2 shows the monthly 4-factor Fama-French-Carhart alpha (using both net-of-expense and gross returns) of mutual funds sorted on two measures of lottery holdings. In the second column of Table A.2 where we proxy the lottery holdings with MAX^{Hold}, the average

alpha decreases monotonically from 0.10% to −0.30% per month from decile 1 to decile 10. This indicates a monthly average return difference of −0.40% between the high- and low-MAX^{Hold} deciles with a Newey-West t-statistic of −3.87, showing that this negative return spread is both economically and statistically significant. This result also indicates that funds in the lowest MAX decile generate 4.80% higher risk-adjusted returns per annum than funds in the highest MAX decile. In the fifth column of Table A.2, where we proxy lottery holdings by $MAX5^{Hold}$, the monthly average alpha spread between the high- and low-MAX^{Hold} deciles is even larger, −0.45% per month (t-stat. = −3.56). The results remain similar for the 4-factor alpha computed from gross returns instead of net-of-expense returns, suggesting that differences in expenses do not drive the return spread.

Next, we investigate the source of the risk-adjusted return difference between the high- and low-MAX^{Hold} portfolios of funds: is it due to outperformance by low-MAX^{Hold} funds, underperformance by high-MAX^{Hold} funds, or both? For this purpose, we focus on the economic and statistical significance of the risk-adjusted returns of decile 1 versus decile 10. As reported in Table A.2, for all lottery holding measures and net-of-expense returns, the 4-factor alphas of funds in decile 10 (high-MAX^{Hold} funds) are significantly negative, whereas the 4-factor alphas of funds in decile 1 (low-MAX^{Hold} funds) are positive but insignificant. Therefore, we conclude that the significantly negative alpha spread between high- and low-MAX^{Hold} funds is largely due to the underperformance by high-MAX^{Hold} funds.

A.1.2 Fama-MacBeth cross-sectional regressions

To the extent that lottery holdings are correlated with a large number of fund characteristics shown in Table 2, multivariate cross-sectional regressions also allow for fund-specific controls. Therefore, we estimate the following Fama-MacBeth regression:

$$\begin{aligned} Alpha_{i,t+1} &= \lambda_{0,t} + \lambda_{1,t} \cdot Alpha_{i,t} + \lambda_{2,t} \cdot MAX_{i,t}^{Hold} + \lambda_{3,t} \cdot MAX_{i,t}^{Fund} \\ &\quad + \textstyle\sum_{k=1}^{K} \lambda_{k,t} \cdot Fund\ Controls_{k,t} + \varepsilon_{i,t+1}. \end{aligned} \tag{A.1}$$

where $Alpha_{i,t+1}$ is the quarterly percentage alpha for fund i in calendar quarter $t+1$ estimated

from the Fama-French-Carhart four-factor model using the daily returns of fund i. $Alpha_{i,t}$ is the alpha in quarter t. $MAX_{i,t}^{Hold}$ is the lottery holdings of fund i in quarter t. Following Goldie, Henry, and Kassa (2018), we define $MAX_{i,t}^{Fund}$ as the maximum daily returns of fund i in the last month of quarter t. $Fund\ Controls_{i,t}$ include the natural log of total net assets (TNA), natural log of fund age, expense ratio, turnover ratio, fund flows, and TNA of the fund's family, all measured as of the end of quarter t. We also include the fund's exposure to SMB, HML, and UMD measured using daily returns during quarter t. All of the independent variables are standardized to a mean of zero with a standard deviation of one. This allows us to interpret the coefficients as the change in next quarter's fund alpha for a one standard deviation change in the independent variable.

Table A.3 presents the average intercept and slope coefficients from the Fama-MacBeth cross-sectional regressions. We report the Newey-West adjusted t-statistics in parentheses. Consistent with our earlier findings from the univariate analysis, model (1) provides evidence of a negative and highly significant relation between MAX^{Hold} and future fund alphas. The average slope on MAX^{Hold} alone is -0.29 with a t-statistic of -2.85, implying that a one standard deviation increase in MAX^{Hold} is associated with a 0.29% decrease in the next quarter's alpha.

[Table A.3 about here]

The signs of slope coefficients on the control variables are consistent with earlier studies. Smaller fund size, lower turnover, and lower expense ratio each have a positive effect on future alpha. Compared with the effect of lottery holdings, the economic significance of a one standard deviation change in any of these fund characteristics is relatively small (0.01% to 0.06% per quarter). As shown in model (4), MAX^{Hold} has an impact on future fund performance even after controlling for past alpha, factor exposures, and a large set of fund characteristics.

Finally, models (5) through (10) control for empirical proxies for the unobservable skill of fund managers and fund characteristics simultaneously, including the return gap measure of Kacperczyk, Sialm, and Zheng (2008), the active share measure of Cremers and Petajisto (2009), the R^2 measure of Amihud and Goyenko (2013), and fund volatility (Jordan and Riley,

2005), all of which have been shown to predict fund performance. In all these specifications, MAX^{Hold} remains a strong predictor of fund performance. Overall, Table A.3 shows that funds with more lottery holdings significantly underperform in the future and this result is robust after controlling for a large number of fund characteristics and other predictors of fund performance.

A.2 Robustness checks

To further corroborate our results in the previous section, we conduct a battery of robustness checks regarding the relation between lottery holdings and future average fund returns. To account for the possibility that small funds may be driving our results, we also report the asset-weighted average return for the portfolios sorted by lottery holdings. Panel A of Table A.4 reports the univariate results. Fama-French-Carhart four-factor alpha spreads between high- and low-MAX portfolios are -0.36% and -0.41% per month and statistically significant for portfolios of funds sorted on MAX^{Hold} and $MAX5^{Hold}$, respectively. Thus, the effect of lottery holdings on fund's future performance is as strong for the asset-weighted fund portfolios as it is for the equally-weighted portfolios in Table A.2, and it does not appear that small funds are driving our findings.

[Table A.4 about here]

In addition to Fama-French-Carhart four-factor alpha, we use the holding-based performance measure and compute characteristic-adjusted returns in Daniel, Grinblatt, Titman, and Wermers (DGTW) (1997). Specifically, "Characteristic Selectivity" (CS) is defined as the difference between the weighted average return of the disclosed fund stock holdings and the weighted average return on one of the 125 passive benchmark portfolios that is matched to each stock in the fund portfolio based on market capitalization, book-to-market ratio, and prior-year return, with the weights being those of the stocks that constitute the funds disclosed holdings. Panel B of Table A.4 shows robust evidence that lottery holdings also negatively predict the benchmark-adjusted fund performance too regardless of the lottery holdings measure we use.

We also investigate lottery holdings and future fund performance by investment style. We classify mutual funds into various investment styles based on the Lipper investment categories from the CRSP mutual fund data available from June 1998. The objective codes include: (i) Mid-Cap, (ii) Small-Cap, (iii) Micro-Cap, (iv) Growth, and (v) Growth and Income. Then, we test if the predictive power of lottery holdings varies among the different styles.

Panel C of Table A.4 presents the univariate portfolio results within each style. Table A.4 shows the four-factor alpha of mutual funds sorted on lottery holdings, proxied by MAX^{Hold}. The first column in Panel C shows that, within the mid-cap funds, the average alpha decreases from 0.26% to −0.21% per month from decile 1 to decile 10. This indicates a monthly average return spread of −0.47% between the high- and low-MAX^{Hold} deciles with a Newey-West t-statistic of −2.82, showing that this negative return spread is both economically and statistically significant. We obtain similar results for other styles as well. The high- and low-MAX^{Hold} decile monthly return spreads for small-cap, micro-cap, growth, and growth and income styles are $-0.55\%, -0.63\%, -0.30\%$, and -0.24%, respectively, all of which are economically and statistically significant. The alpha spread is most pronounced in micro- and small-cap funds.

Finally, we use three alternative lottery holding measures and examine their relations to future fund performance. The first measure, $MAXProp$, is the proportion of fund's assets that is invested in lottery stocks (i.e., stocks whose MAX is in the top quintile among all stocks). Specifically, we construct quintiles of all common stocks in the CRSP stock database by sorting stocks in ascending order according to their maximum daily returns. The first (fifth) quintile consists of stocks that achieve the lowest (highest) maximum daily returns. $MAXProp$ corresponds to the proportion of the fund's assets invested in the stocks belonging to the fifth quintile. The second measure, $Top\ 10\ MAX^{Hold}$, is the holding-weighted lottery measure (i.e., MAX of the stocks) for the top 10 stocks held by the funds based on their investments. We focus on the top 10 stocks because when faced with a long list of fund holdings, investors may only respond to the top holdings of a fund. Therefore, we compute $Top\ 10\ MAX^{Hold}$ by first sorting all stocks held by the fund at quarter ends based on their values in the fund's portfolio. We then calculate the holding-weighted lottery measure for

only the top 10 stocks. The third measure, the lottery index ($LTRY$), is a composite index of lottery-likeness following Kumar (2009) and Bali, Hirshleifer, Peng, and Tang (2018), who define lottery-like stocks as those with low-price, high idiosyncratic volatility, and high idiosyncratic skewness.[24]

Panel D of Table A.4 reports the results using alternative measures of lottery holdings.The Fama-French-Carhart four-factor alpha spreads between high- and low-MAX portfolios are -0.30%, -0.31%, and -0.27% per month and statistically significant for portfolios of funds sorted on $MAXProp$, $Top\ 10\ MAX^{Hold}$, and $LTRY$, respectively. Thus, the effect of lottery holdings on a fund's future performance is robust to the use of alternative measures of lottery holdings.

A.3 Controlling for other predictors of fund performance

A.3.1 Alpha

There is a potential concern that the predicability of lottery holdings for funds' future performance is attributable to other predictors identified in the prior literature. The predictive power of lottery holdings could be driven by the short-term persistence documented in Bollen and Busse (2005). Thus, in the empirical analyses to follow, we investigate the predictive power of lottery holdings after controlling for *Alpha*, the quarterly percentage alpha calculated from the Fama-French-Carhart four-factor model using daily returns following Bollen and Busse (2005).

To explore the relation between lottery holdings and *Alpha*, column (1) of Table A.5 shows the results for a conditional bivariate portfolio test for lottery holdings by controlling

[24]Following Bali, Hirshleifer, Peng, and Tang (2018), each month we sort stocks into 50 bins by price (PRC) per share in descending order such that stocks in the lowest (highest) bin have the highest (lowest) last day ending price per share. We also independently sort stocks into 50 bins by idiosyncratic volatility (IVOL) and by idiosyncratic skewness (ISKEW) in ascending order. We estimate IVOL and ISKEW from the time-series regression of daily stock returns against the daily stock market factor in a month. IVOL is the standard deviation of the residuals from the regression and ISKEW is the skewness of residuals from the same regression. We construct the lottery index, denoted by LTRY, by summing up the ranks of the PRC, IVOL, and ISKEW portfolios. By construction, the lottery index has an integer value in the range of 3 to 150, and it increases with a stock's lottery feature. Our results are similar if we calculate IVOL and ISKEW from the time-series regression of daily stock returns against the daily stock market, size, and book-to-market factors.

for *Alpha*. Table A.5 shows that the average spread in the monthly four-factor alphas between decile 10 and 1 is -0.30% (t-stat. $= -2.88$) after controlling for past month's alphas. Thus, the predictive power of MAX^{Hold} for future fund performance is not driven by the short-term performance persistence documented in Bollen and Busse (2005).

[Table A.5 about here]

A.3.2 Proxies of managerial skill

We next examine if lack of managerial skill can explain our findings of worse future performance of funds with more lottery holdings. We rely on the extant literature that use empirical proxies to identify the unobservable skill of fund managers. These include the return gap measure of Kacperczyk, Sialm, and Zheng (2008), the active share measure of Cremers and Petajisto (2009), and the R^2 measure of Amihud and Goyenko (2013).[25] The return gap is the difference between a fund's realized gross return and the hypothetical return of its most recently disclosed portfolio holdings. A higher return gap has been shown to predict better fund performance. The active share measure (Cremers and Petajisto, 2009) is the sum of the absolute deviations between a fund's holdings and benchmark holdings. This measure has been shown to be positively related to future fund performance. The R^2 measure is calculated from regressing the fund's monthly returns over twenty-four months using the Fama-French four-factor model. A lower R^2 predicts better fund performance.

Columns (2) to (4) of Table A.5 shows that the predictive power of MAX^{Hold} is not subsumed by those of different predictors of fund performance. Specifically, we find that the average alpha difference between decile 10 and 1 is -0.34% per month with a t-statistic of -3.17 after controlling for the return gap, -0.43% per month (t-stat. $= -3.65$) after controlling for the active share, and -0.32% per month (t-stat. $= -3.08$) per month after controlling for the R^2. So, while the unobserved actions of mutual funds (measured by return gap) or stock selectivity (measured by either active share or R^2) may predict fund performance,

[25] Sockin and Zhang (2018) provide theoretical support for the active share and return gap as measures of manager skill. Lan, Moneta, and Wermers (2018) investigate how holding horizon provides independent predictive power for fund returns from the aforementioned empirical measures of manager skill.

that ability does not appear to explain the difference in fund performance attributable to differences in funds' holdings of lottery stocks.

A.3.3 Fund volatility

Funds with high lottery holdings in a given quarter are likely to have high realized volatility in the same quarter. Jordan and Riley (2015) show that fund return volatility has a significant negative effect on funds' future performance. Therefore, it is plausible that MAX^{Hold} is proxying for this effect. In addition, fund volatility is related to managerial ability given the evidence shown in Kaniel, Tompaidis, and Zhou (2018), who find that volatility of funds decreases as managerial ability increases.[26] We next examine these possibilities. Following Jordan and Riley (2015), we first estimate the volatility of each fund using its daily returns over the past one year. We then conduct bivariate sorts. In column (5) of Table A.5, we sort on fund lottery holdings after controlling for fund-level volatility. We first form decile portfolios based on fund-level volatility (VOL^{Fund}), and within each volatility decile, we sort funds further into decile portfolios based on MAX^{Hold}. The last row in the last column of Table A.5 shows the 4-factor alpha differences between the low- and high-MAX^{Hold} portfolios, i.e., the differences between returns on portfolios that vary substantially in lottery holdings but have approximately the same levels of fund volatility. Column (5) of Table A.5 shows that the $10-1$ difference is -0.26% per month, and highly significant (t-stat. $= -2.78$). These magnitudes are smaller than the univariate sort results in Table A.2, but that is hardly surprising. Fund volatility and fund lottery holdings are positively correlated. Therefore, after controlling for volatility, the spread in the performance of funds with highest and lowest lottery holdings should reduce. However, we observe that fund-level volatility does not completely explain the high (low) returns to low (high) MAX^{Hold} funds.

[26] They show what drives this result is the change in managerial behavior when ability changes: managers with higher levels of ability can choose fund allocations that achieve the same expected returns at lower levels of idiosyncratic volatility.

Table A.1: Descriptive summary statistics for alternative lottery holding measures

This table reports the summary statistics for three alternative lottery holding measures. $MAXProp$ is average monthly proportion of fund's assets that is invested in lottery stocks (i.e., stocks whose MAX is in the top quintile among all stocks) during a quarter. $Top\ 10\ MAX^{Hold}$ is the average monthly holding-weighted lottery measure (i.e., MAX of the stocks) for the top 10 stocks held by the funds based on their investments during a quarter. $LTRY$ is the composite lottery index of lottery-likeness following Kumar (2009) and Bali, Hirshleifer, Peng, and Tang (2018), who define lottery-like stocks as those with low-price, high idiosyncratic volatility, and high idiosyncratic skewness. Panel B shows the average characteristics of portfolios of mutual funds in the portfolio formation quarter by each of the three lottery holding measures. At the beginning of each calendar quarter, we form decile portfolios of mutual funds based on their lottery holdings. Decile 1 contains funds with the lowest lottery holdings and decile 10 contains funds with the highest lottery holdings. We also present results for the fifth lottery holdings decile. The corresponding t-statistic to test the difference in means is provided for each lottery holding measure.

Variable	N	Mean	Median	Q1	Q3
Panel A: Quarterly lottery holding measures (%)					
MAXProp	87,613	0.05	0.03	0.01	0.07
Top 10 MAX^{Hold}	87,613	4.50	3.78	2.86	5.32
LTRY	87,607	46.04	44.05	37.67	53.05

Panel B: Fund characteristics					
Low MAXProp	0.01	Low Top 10 MAX^{Hold}	2.69	Low LTRY	32.25
5	0.03	5	3.83	5	41.93
High MAXprop	0.16	High Top 10 MAX^{Hold}	7.71	High LTRY	67.10
Difference	0.15	Difference	5.02	Difference	34.86
t-stat	25.41	t-stat	10.52	t-stat	28.24

Table A.2: Univariate portfolio of mutual funds sorted on lottery holdings

This table reports the monthly Fama-French-Carhart (FFC) four-factor alpha from both gross returns and net-of-expense returns on portfolios of mutual funds sorted on two measures of lottery holdings. At the beginning of each calendar quarter from January 2000 to December 2014, we form decile portfolios of mutual funds based on the two measures of lottery holdings, MAX^{Hold} or MAX5^{Hold}. Decile 1 contains funds with the lowest lottery holdings and decile 10 contains funds with the highest lottery holdings. Each portfolio is equal-weighted and has the same number of funds at the start of each quarter. A fund remains in the same portfolio for the next three months and then rebalance. The alphas are in monthly percentage. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

		FFC 4-factor alphas from			FFC 4-factor alphas from	
Deciles	MAX^{Hold}	Net-of-expense returns	Gross-of-expense returns	MAX5^{Hold}	Net-of-expense returns	Gross-of-expense returns
Low	3.16	0.10	0.19***	1.97	0.12*	0.22***
		(1.44)	(2.83)		(1.78)	(3.23)
2	3.54	0.03	0.12**	2.19	0.04	0.14**
		(0.52)	(2.25)		(0.68)	(2.28)
3	3.75	0.02	0.11**	2.31	-0.01	0.10**
		(0.40)	(2.39)		(-0.13)	(2.07)
4	3.94	-0.01	0.08	2.42	-0.03	0.08
		(-0.29)	(1.62)		(-0.57)	(1.54)
5	4.17	-0.01	0.08	2.55	-0.03	0.08
		(-0.23)	(1.34)		(-0.37)	(1.27)
6	4.46	0.00	0.11	2.71	0.00	0.11
		(0.05)	(1.48)		(0.03)	(1.70)
7	4.82	-0.01	0.10	2.91	0.00	0.12
		(-0.09)	(1.48)		(0.01)	(1.58)
8	5.26	-0.03	0.08	3.15	-0.01	0.09
		(-0.35)	(1.12)		(-0.18)	(1.31)
9	5.84	-0.16**	-0.05	3.47	-0.14*	-0.04
		(-2.54)	(-0.80)		(-1.74)	(-0.61)
High	7.08	-0.30***	-0.18**	4.11	-0.33***	-0.25**
		(-3.40)	(-2.08)		(-3.08)	(-2.45)
High − Low	3.92***	-0.40***	-0.38***	2.13***	-0.45***	-0.46***
	(10.04)	(-3.87)	(-3.66)	(8.07)	(-3.56)	(-3.82)

Table A.3: Does fund lottery holdings predict future fund performance?

This table reports the average slope coefficients from the Fama and MacBeth (1973) cross-sectional regressions from the model

$$Alpha_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot Alpha_{i,t} + \lambda_{2,t} \cdot MAX_{i,t}^{Hold} + \lambda_{3,t} \cdot MAX_{i,t}^{Fund} + \sum_{k=1}^{K} \lambda_{k,t} \cdot Fund\ Controls_{k,t} + \varepsilon_{i,t+1}.$$

The dependent variable is the quarterly percentage alpha for fund i in calendar quarter $t+1$ calculated from the Fama-French-Carhart four-factor model using daily returns within a quarter. Alpha$_{i,t}$ is the same alpha in the prior quarter. Fund lottery holdings in this table is measured by MAX^{Hold}, the holding-weighted lottery characteristics using stock maximum daily returns within the current month. MAX$_{i,t}^{Fund}$ is the maximum daily returns of fund i in the last month of quarter t. Fund controls include the natural log of assets, natural log of age, expense ratio, turnover ratio, fund flows, and TNA family, all measured as of the end of quarter t. We also control for Fama-French-Carhart SMB (size), HML (value), and UMD (momentum) exposures calculated from daily returns during prior quarter. Other control variables include return gap, active share, fund R^2, and fund volatility (VOL^{Fund}), all measured as of the end of quarter t. All right-hand variables are z-scored (demeaned and divided by their standard deviation) within each quarter. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
MAX^{Hold}	-0.29***		-0.25**	-0.24**	-0.21**	-0.20**	-0.19**	-0.18**	-0.22***	-0.32**
	(-2.85)		(-2.79)	(-2.75)	(-2.56)	(-2.49)	(-2.38)	(-2.35)	(-2.69)	(-2.62)
MAX^{Fund}		-0.22**	-0.11	-0.10	-0.16	-0.13	-0.14	-0.11	-0.07	-0.06
		(-2.25)	(-1.06)	(-0.89)	(-1.34)	(-1.14)	(-1.20)	(-1.24)	(-0.59)	(-0.64)
Alpha				0.22***	0.19**	0.23**	0.20**	0.19**	0.21**	0.18**
				(2.93)	(2.02)	(2.51)	(2.43)	(2.41)	(2.36)	(2.10)
log(TNA)				-0.05***						-0.06***
				(-3.19)						(-2.72)
log(Age)				0.01						0.02
				(1.34)						(1.14)
Expense				-0.08***						-0.09***
				(-3.66)						(-4.53)
Turnover				-0.06**						-0.09**
				(-2.32)						(-2.12)
Flow				0.01						0.01
				(1.33)						(0.67)
TNA family				0.05						0.03
				(1.48)						(0.77)
β^{SMB}				0.19**						0.25*
				(2.00)						(2.00)
β^{HML}				0.22**						0.29**
				(2.13)						(2.24)
β^{UMD}				-0.26**						-0.32**
				(-2.42)						(-2.60)
Return gap					0.08**				0.08**	0.07**
					(2.13)				(2.05)	(2.30)
Active share						0.14**			0.21***	0.11*
						(2.40)			(3.21)	(1.80)
R^2							0.02		0.21*	0.04
							(0.42)		(1.99)	(0.57)
VOL^{Fund}								-0.15**	-0.16*	-0.20*
								(-2.06)	(-1.82)	(-1.98)
Fund-quarter obs	96,302	95,510	95,510	94,691	76,969	84,519	94,533	94,691	76,963	76,963
# of quarters	61	61	61	61	61	61	61	61	61	61
Average R-squared	0.04	0.04	0.07	0.20	0.12	0.11	0.11	0.12	0.16	0.24

Table A.4: Robustness checks

Panel A reports the monthly Fama-French-Carhart four-factor alpha on portfolios of mutual funds sorted on lottery holdings, using fund assets as weights. Panel B reports the univariate portfolio results using monthly characteristic-adjusted returns (DGTW, 1997). Panel C presents the monthly Fama-French-Carhart four-factor alpha on portfolios sorted on lottery holdings within investment style. Fund lottery holdings in Panel C is measured by MAX^{Hold}, the holding-weighted lottery characteristics using stock maximum daily returns within the current month. We classify funds into various investment styles based on the Lipper investment categories: (i) Mid-Cap funds, (ii) Small-Cap funds, (iii) Micro-Cap funds, (iv) Growth funds, (v) Growth and Income funds. We present results for decile 1 (low lottery holdings), the fifth decile, and decile 10 (high lottery holdings). Panel D uses three alternative measures of lottery holdings and reports the monthly Fama-French-Carhart four-factor alpha on portfolios of mutual funds sorted on these alternative measures. $MAXProp$ is the proportion of fund's assets that is invested in lottery stocks (i.e., stocks whose MAX is in the top quintile among all stocks). *Top 10* MAX^{Hold} is the holding-weighted lottery measure (i.e., MAX of the stocks) for the top 10 stocks held by the funds based on their investments. $LTRY$ is an composite index of lottery-likeness. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Asset-weighted portfolios

	MAX	MAX5
Low	0.02	0.10
	(0.91)	(1.67)
5	-0.06	-0.06
	(-1.00)	(-0.88)
High	-0.34***	-0.31***
	(-3.16)	(-3.09)
High − Low	-0.36***	-0.41***
	(-2.79)	(-3.21)

Panel B: Characteristic-adjusted returns

	MAX	MAX5
Low	0.06	0.07
	(0.77)	(0.83)
5	0.01	0.00
	(0.23)	(0.03)
High	-0.29**	-0.32**
	(-2.43)	(-2.49)
High − Low	-0.35**	-0.38**
	(-2.60)	(-2.69)

Panel C: Across different investment styles

	Mid-cap	Small-cap	Micro-cap	Growth	Growth and Income
Low	0.26***	0.21**	0.24	0.03	0.11
	(2.79)	(2.05)	(1.09)	(0.54)	(0.35)
5	0.00	-0.02	0.15	-0.09	-0.07
	(-0.05)	(-0.31)	(0.83)	(-1.56)	(-0.18)
High	-0.21	-0.34***	-0.39*	-0.27**	-0.13*
	(-1.39)	(-3.28)	(-1.78)	(-1.97)	(-1.74)
High − Low	-0.47***	-0.55***	-0.63**	-0.30**	-0.24*
	(-2.82)	(-4.24)	(-2.35)	(-2.15)	(-1.97)

Panel D: Alternative measures of lottery holdings

	MAXProp	Top 10 MAX^{Hold}	LTRY Index
Low	0.12	0.08	0.10
	(1.17)	(1.32)	(0.43)
5	-0.04	0.00	-0.03
	(-0.74)	(0.06)	(-0.40)
High	-0.26***	-0.24***	-0.17**
	(-2.85)	(-2.87)	(-2.16)
High − Low	-0.30**	-0.31***	-0.27**
	(-2.31)	(-3.81)	(-2.58)

Table A.5: Bivariate portfolios of fund lottery holdings controlling for other fund performance predictors

This table reports the Fama-French-Carhart four-factor alpha on portfolios of mutual funds sorted on lottery holdings after controlling for other fund performance predictors. In each quarter, we first sort funds into quintiles using the control variable, then within each quintile, we sort funds into decile portfolios based on fund lottery holdings over the previous quarter so that decile 1 (10) contains funds with the lowest (highest) lottery holdings. This table presents monthly alphas across the ten control deciles to produce decile portfolios with dispersion in lottery holdings but with similar levels of the control variable. Fund lottery holdings in this table is measured by MAX^{Hold}, the holding-weighted lottery characteristics using stock maximum daily returns within the current month. Alpha is the quarterly percentage alpha calculated from the Fama-French-Carhart four-factor model using fund daily returns. Return gap is defined as the moving average of 12 monthly return gaps as in Kacperczyk, Sialm, and Zheng (2008). Active share measures the percentage of fund holdings that is different from the benchmark holdings, following Cremers and Petajisto (2009). R-square (R^2) is the Fama-French-Carhart four-factor model with a twenty-four-month estimation period, following Amihud and Goyenko (2013). Fund volatility (VOL^{Fund}) is defined as the standard deviation using past one-year daily fund returns, following Jordan and Riley (2015). The alphas are in monthly percentage. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
	Alpha	Return gap	Active share	R^2	VOL^{Fund}
Low MAX^{Hold}	0.09	0.10	0.13	0.09	0.08
	(1.34)	(1.37)	(1.57)	(1.38)	(0.86)
2	0.04	0.03	0.12	0.06	0.01
	(0.59)	(0.44)	(1.51)	(1.04)	(0.19)
3	-0.00	-0.02	0.08	0.03	-0.01
	(-0.01)	(-0.38)	(0.93)	(0.51)	(-0.10)
4	-0.03	-0.01	0.09	0.02	-0.01
	(-0.52)	(-0.19)	(1.18)	(0.26)	(-0.10)
5	-0.02	-0.02	0.04	-0.01	-0.05
	(-0.37)	(-0.28)	(0.49)	(-0.17)	(-0.85)
6	-0.05	-0.01	-0.05	-0.05	-0.03
	(-0.79)	(-0.07)	(-0.63)	(-0.79)	(-0.55)
7	-0.05	-0.01	-0.05	-0.02	-0.05
	(-0.62)	(-0.07)	(-0.73)	(-0.27)	(-0.97)
8	-0.05	-0.04	-0.11	-0.08	-0.07
	(-0.70)	(-0.49)	(-1.59)	(-1.24)	(-1.02)
9	-0.10	-0.07	-0.16*	-0.11	-0.09
	(-1.40)	(-0.82)	(-1.89)	(-1.48)	(-1.51)
High MAX^{Hold}	-0.21**	-0.24**	-0.30***	-0.22**	-0.18*
	(-2.32)	(-2.43)	(-3.35)	(-2.50)	(-1.91)
High − Low	-0.30***	-0.34***	-0.43***	-0.32***	-0.26***
	(-2.88)	(-3.17)	(-3.65)	(-3.08)	(-2.78)

Table A.6: Bivariate portfolios of fund lottery holdings (MAX^{Hold}) and fund daily maximum (MAX^{Fund})

This table reports the Fama-French-Carhart four-factor alpha on bivariate portfolios of mutual funds sorted on fund lottery holdings (MAX^{Hold}) and fund daily maximum ((MAX^{Fund}). The results show that MAX^{Fund} does not predict fund future performance after controlling for MAX^{Hold}, while MAX^{Hold} remains a strong and negative predictor even after controlling for MAX^{Fund}. In Panel A, for each quarter we first sort funds into quintiles based on MAX^{Fund}, then within each quintile, we sort funds into decile portfolios based on fund lottery holdings (MAX^{Hold}) over the previous quarter so that decile 1 (10) contains funds with the lowest (highest) lottery holdings. In Panel B, we conduct a reverse sequential sort by first sorting funds into quintiles based on MAX^{Hold}, then within each quintile, we sort funds into decile portfolios based on fund maximum daily returns (MAX^{Fund}). MAX^{Hold} is the holding-weighted lottery characteristics using stock maximum daily returns within the current month. MAX^{Fund} is the fund daily maximum return in the last month over the previous quarter. The alphas are in monthly percentage. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: First sort on MAX^{Fund} then MAX^{Hold}

Low MAX^{Hold}	2	3	4	5	6	7	8	9	High MAX^{Hold}	High − Low
0.07	-0.01	-0.03	-0.04	-0.05	-0.04	-0.00	-0.02	-0.13*	-0.21**	-0.27**
(1.20)	(-0.28)	(-0.63)	(-0.80)	(-0.91)	(-0.67)	(-0.06)	(-0.33)	(-1.93)	(-2.24)	(-2.78)

Panel B: First sort on MAX^{Hold} then MAX^{Fund}

Low MAX^{Fund}	2	3	4	5	6	7	8	9	High MAX^{Fund}	High − Low
0.02	0.01	0.00	-0.03	-0.07	-0.08	-0.06	-0.08	-0.08	-0.09	-0.11
(0.59)	(0.13)	(0.04)	(-0.41)	(-1.07)	(-1.30)	(-0.79)	(-1.82)	(-0.82)	(-0.97)	(-1.02)