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Abstract

We provide evidence regarding mutual funds' motivation to hold lottery stocks. Funds with higher managerial ownership invest less in lottery stocks, suggesting that managers themselves do not prefer such stocks. The evidence instead supports that managers cater to fund investors' preference for such stocks. In particular, funds with more lottery holdings attract larger flows after portfolio disclosure compared to their peers, and poorly performing funds tend to engage in risk shifting by increasing their lottery holdings towards year-ends. Funds' aggregate holdings of lottery stocks contribute to their overpricing.

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I. Introduction

There is abundant evidence that some investors prefer "lottery stocks" despite the fact that they tend to significantly underperform other stocks (see, e.g., Kumar (2009), Bali, Cakici and Whitelaw (2011), Han and Kumar (2013), and Conrad, Kapadia and Xing (2014)). A plausible explanation is that investors' preference for a small chance of a large payoff is strong enough to lead to overvaluation of these assets. Goldie, Henry and Kassa (2019) and Akbas and Genc (2020) show that lottery preferences also extend to mutual fund investors as their investment flows respond strongly to extreme positive fund returns. We contribute to this literature by assessing whether fund managers select lottery stocks i) to cater to fund investors' preferences for lottery-like returns, ii) to satisfy their own preferences for such returns, or iii) due to strategic risk-shifting considerations. We also assess whether investor sophistication plays a role in observed outcomes. Finally, we examine whether the aggregate lottery holdings of institutional investors influence the valuation of lottery stocks.

Following Bali et al. (2011) and Bali, Brown, Murray and Tang (2017), we use two ex-ante "lotteryness" measures, MAX and MAX5. MAX is the single highest daily return of a stock within a calendar month, and MAX5 is the average of the five highest daily returns within a calendar month. We then construct a quarterly fund-level measure of lottery holdings using the holdings-weighted average of the MAX and MAX5 measures across all stocks in a fund's portfolio. 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 earn lower future returns. Given the detrimental effect on fund performance of holding lottery stocks, we address the primary question in this study: why do mutual funds invest in lottery stocks?

We begin our empirical investigation by testing the hypothesis that mutual funds invest in lottery stocks because their investors prefer lottery-like returns. Although fund investors' preferences are not directly observable, we follow Barber, Huang and Odean (2016) and Berk and van Binsbergen (2016) to use net flows as a proxy for investors' revealed preferences. We find that funds with higher lottery holdings are smaller in size, younger, and have relatively poor past performance. Funds with these characteristics have high incentives to attract more flows, and one obvious way of attracting more flows is to cater to investors' preferences for lottery stocks. To test the hypothesis more formally, we follow Sirri and Tufano (1998) to estimate a piecewise linear regression of flows. We find that even after controlling for past performance and a host of fund characteristics, funds with more lottery holdings receive significantly higher net flows from their investors. Ceteris paribus, a one-standard-deviation quarterly increase in a fund's lottery holdings is associated with a 12% to 19% increase in fund flows in the next quarter. These results hold even after controlling for investors' preferences for recent winner stocks (Agarwal, Gay and Ling (2014)) and extreme positive payoffs of funds (see, e.g., Goldie et al. (2019) and Akbas and Genc (2020)). These findings are also robust to the use of alternative measures of lottery holdings, including the proportion of a fund's holdings that is invested in lottery stocks, and the MAX and MAX5 measures applied only to the 10 largest holdings in a fund that are more easily observable to fund investors.

We next examine whether less sophisticated investors have the same preference for lottery stocks as more sophisticated investors. Prior literature suggests that funds' distribution channels can proxy for investor sophistication. For example, Del Guercio and Reuter (2013), Chalmers and Reuter (2012), and Barber et al. (2016) find that investors of direct-sold funds are more sophisticated than investors in broker-sold funds. We find that lottery holdings of broker-sold funds attract 10% more flows than those of direct-sold funds. This suggests that funds that invest more heavily in lottery stocks draw less sophisticated clientele. This evidence complements prior studies that document retail investors' predisposition to lottery stocks (see, e.g., Kumar (2009), Kumar, Page and Spalt (2011), Doran, Jiang and Peterson (2012), Conrad et al. (2014), and Bali et al. (2017)).

To investigate our claim that investor flows respond to funds' lottery holdings (rather than to potentially omitted variables or unobserved factors), we focus on the period around the dates on which funds publicly disclose their portfolio positions. We use filing dates of holdings reports from the Securities and Exchange Commission (SEC) EDGAR database to employ a difference-in-differences (DID) approach, and we find that funds with more lottery holdings attract significantly more flows after disclosure. In contrast, prior to disclosure, there is no significant difference in the average monthly flows between funds with more lottery holdings (the treatment group) and funds with less lottery holdings (the control group). These findings are robust to the use of actual daily flows from the Trimtabs database in place of estimated monthly flows from the CRSP Survivorship Bias Free Mutual Fund Database.

Our analyses reveal both costs and benefits associated with funds' investments in lottery stocks. On one hand, funds with more lottery holdings bear costs in terms of worse future performance, and therefore lower fund flows. On the other hand, these funds benefit from higher flows by catering to their investors' preferences. Moreover, the sensitivity of flows to past performance as well as the sensitivity of flows to lottery holdings are the highest for best performing funds. A back-of-the-envelope cost-benefit analysis shows that funds with worst and mid-range performance have stronger incentives to hold lottery stocks because benefits outweigh costs at a lower threshold of lottery holdings. In contrast, best performing funds would need to invest substantially more in lottery stocks for benefits to outweigh costs, which may not be feasible.

A natural question is whether in predicting a fund's future performance, investors would be better off assessing the distribution of a fund's past returns or the fund's lottery holdings. We address this question by comparing the predictive power of a fund's lottery holdings with that of a fund's past lottery-like returns. Our results show that funds' lottery holdings significantly predicts funds' lottery-like returns over a longer period (for at least one year). In contrast, the predictive power of past lottery-like fund returns is shorter and lasts only for four months.

Given that, on average, funds with more lottery stock holdings perform worse in the future, a priori it is difficult to conceive that fund managers would exhibit as great a preference for lottery stocks as their investors. However, there is recent evidence that behavioral biases and agency problems drive fund managers to buy overvalued stocks, including lottery stocks. For example, Edelen, Ince and Kadlec (2016) show that agency-induced preferences can explain the tendency of institutional investors to buy overvalued stocks that are found in the short legs of anomalies. Brown, Lu, Ray and Teo (2018) show that sensation-seeking hedge fund managers often take higher risks and exhibit preferences for lottery stocks. The contrasting view is that institutional investors are "smart" and sophisticated and therefore would avoid holding lottery stocks. To disentangle managers' and investors' lottery stock preferences, we investigate how a fund manager's stake in a fund affects a fund's tendency to invest in lottery stocks. We find that managers tend to avoid lottery stocks when their ownership in funds is high, suggesting that managers themselves do not prefer lottery stocks.

We next explore the possibility that fund managers invest in lottery stocks towards the end of the year to improve their probability of "winning", i.e., achieving high returns relative to their peers. Such risk-shifting behavior is symptomatic of agency problems in mutual funds and has been widely documented in the literature.[1] Literature on tournaments and the convexity of the flow-performance relation (see, e.g., Brown et al. (1996), Chevalier and Ellison (1997), Sirri and Tufano (1998), and Huang, Wei and Yan (2007)) suggests that investors typically evaluate equity mutual 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 provide incentives to poorly performing funds to increase their risk toward year end to "catch up" to their peers. We find evidence consistent with such risk-shifting behavior, i.e., fund managers with poor performance earlier in the year tend to disproportionally increase their positions in lottery stocks as the calendar year comes to a close.

Finally, motivated by the prior research on the influence of aggregate institutional trading on stock returns (see, e.g., Nofsinger and Sias (1999), Wermers (1999, 2000), and Parrino, Sias and Starks (2003)), we explore the asset pricing implications of mutual funds holding lottery stocks. We find that a decrease in institutional demand is associated with stronger underperformance of such stocks, consistent with institutional investors selling lottery stocks and retail investors buying them. We also hypothesize that if mutual funds disproportionately purchase

[1]This literature includes the window-dressing behavior among portfolio managers (see, e.g., Lakonishok, Shleifer, Thaler and Vishny (1991), He, Ng and Wang (2004), Ng and Wang (2004), and Agarwal et al. (2014)), strategic risk-shifting motivated by agency issues (see, e.g., Brown, Harlow and Starks (1996), Chevalier and Ellison (1997), Kempf, Ruenzi and Thiele (2009), Hu, Kale, Pagani and Subramanian (2011), Huang, Sialm and Zhang (2011), and Schwarz (2012)), conflict of interests arising from offering multiple products (see, e.g., Gaspar, Massa and Matos (2006), Chen and Chen (2009), Cici, Gibson and Moussawi (2010), and Bhattacharya, Lee and Pool (2013)) and incentive misalignment due to business ties (see, e.g., Davis and Kim (2007), Cohen and Schmidt (2009), and Ashraf, Jayaraman and Ryan (2012)).

lottery stocks, the resulting price pressure should contribute to these stocks' overvaluation. We find support for this hypothesis, thereby implying a more negative lottery demand factor return in the stock market.

Our study makes several contributions. First, we provide new evidence on costs and benefits arising from mutual fund investment in lottery stocks. Funds suffer worse future performance when they invest in lottery stocks but benefit from more flows. This finding holds even after controlling for extremely positive prior fund return. Our findings therefore complement those of Akbas and Genc (2020) and show that funds invest in lottery stocks to cater to their investors' preferences for stocks that can present the possibility of achieving extreme payoffs. Second, our study uncovers a new channel, namely investment in lottery stocks, through which funds can engage in risk-shifting behavior in an attempt to outperform their peers and attract more capital. Finally, our study provides novel evidence on asset pricing implications of mutual funds holding lottery stocks.

II. Data and Variable Construction

A. Data

For U.S. open-end mutual funds, we obtain returns and fund characteristics such as total net assets (TNA), expense ratio, and turnover ratio from the Center for Research in Security Prices (CRSP) Survivorship Bias Free Mutual Fund Database. We start our sample period in January 2000 and end it in February 2018.[2] We estimate monthly fund flows as the change of TNA from month to month (excluding the change in asset size due to fund returns). We compute fund-level total net assets as the sum of TNA across all share classes of a fund. Return, expense ratio, turnover ratio, and flow are TNA-weighted averages across all share classes. Fund age is

[2] Although mutual fund holdings data are available beginning in January 1980, our sample period starts in January 2000 because we require daily fund returns 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 daily fund returns as in Jordan and Riley (2015). Our sample period ends in February 2018, the latest date for which MFLINKS tables are available in Wharton Research Data Services (WRDS) to merge the CRSP Mutual Fund database and the Thomson Reuters Mutual Fund Holdings database.

the number of years since the inception of the oldest share class in the fund. Since we include fund size as another independent control variable, the size of a fund family ($ billion) is the sum of TNA of all funds in the family excluding the fund's TNA itself. We select funds in our sample from the CRSP mutual fund data using objective codes as in 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 80% of assets under management to be in common stocks. We restrict our sample to funds that are at least a year old and have at least $20 million in assets. We eliminate all the data prior to the fund's ticker creation date to mitigate the incubation bias as suggested in Evans (2010). We use net-of-fee fund returns to focus on the actual performance of investors.

We obtain each fund's investment objective code and share volume of portfolio holdings from the Thomson Reuters Mutual Fund Holdings S12 database. Weighting by the value of the holding in the fund's portfolio, we calculate the fund-level stock holding characteristics from the CRSP and Compustat datasets. These characteristics include 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 remove funds with an investment objective code of 1, 5, 6, 7, or 8, which correspond to 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 use Thomson Reuters Institutional (13f) Holdings S34 data to measure the change in the number of institutional investors for each stock.

Finally, for a more in-depth analysis on the timing of capital flows, we use data on daily flows from the TrimTabs database. While CRSP provides 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, the Trimtabs provides *actual* net flows (in dollars) and TNA at a much higher (daily) frequency. Daily flows from Trimtabs are therefore not subject to measurement error as in the case of flows imputed from funds' assets and returns.[3] However,

[3]Following Greene and Hodges (2002), Rakowski (2010), and Kaniel and Parham (2017), we calculate the daily fund flows as the ratio of dollar flows to prior day's TNA.

the TrimTabs dataset relies on voluntary disclosure by funds and therefore has limited coverage of funds compared with the CRSP sample. To precisely identify the date when funds' portfolio holdings become available to investors, we obtain actual filing dates of funds' holdings using the dataset shared by Schwarz and Potter (2016) which is available through December 2009.[4] Between January 2010 and February 2018 (end of our sample period), we use the median delay period of 60 days from the report date to infer the filing date.

B. Measures of lottery characteristics

Following Bali et al. (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. 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. Using portfolio weights in the last month of each quarter, we construct the holding-weighted lottery characteristics to obtain a fund-level measure of lottery holdings: MAX^{Hold} and $\text{MAX5}^{\text{Hold}}$.[5]

Table 1 reports summary statistics and correlation coefficients of the key variables used in our empirical analyses. In Panel A, we report summary statistics for the fund-level lottery holding measures. The mean values for MAX^{Hold} and $\text{MAX5}^{\text{Hold}}$ are 4.30% and 2.56%, respectively. The MAX^{Hold} value of 4.30% indicates that, on average, the maximum daily return of the holdings in our sample of funds over the course of a calendar month is 4.30%. A similar interpretation applies to the $\text{MAX5}^{\text{Hold}}$ figure of 2.56%, except that MAX5 represents the average of the five highest daily returns in a calendar month.

[4] We thank Chris Schwarz for providing this data.

[5] For robustness, we use three alternative lottery holding measures. The first measure, MAX_PROP, is the proportion of a fund's stock holdings that is invested in stocks whose lotteryness as measured by MAX is in the top quintile among all stocks. The second measure, $\text{TOP10\_MAX}^{\text{Hold}}$, is the holding-weighted average lotteryness, again as measured by MAX, for the top 10 stocks held by funds. The third measure, LTRY, is a composite index of lotteryness following Kumar (2009) and Bali et al. (2019) who define lottery stocks as those with low-price, high idiosyncratic volatility, and high idiosyncratic skewness. The correlations between MAX^{Hold} and $\text{MAX5}^{\text{Hold}}$ and other lottery holding proxies are high, ranging between 0.81 and 0.87. Our results are similar when we use these alternative measures.

C. Other key variables

Panel B also reports summary statistics for other key variables. We define alpha as the quarterly percentage alpha estimated from the Fama-French-Carhart (FFC) four-factor model using daily fund returns. Panel B shows that the mean (median) quarterly alpha is -0.38% (-0.20%). The average fund TNA is $1,471 million and the average fund age is 12.98 years. The average annual expense ratio is 1.14%. The average annual turnover ratio as reported in the CRSP data is 92.51%. Finally, the average quarterly fund flow is 3.23%.

Panel C provides correlations between the key variables. Not surprisingly, the two lottery holding measures are strongly correlated, exhibiting a positive coefficient of 0.87. 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, $\text{MAX5}^{\text{Hold}}$. We also find that the two lottery holding measures are negatively related to fund size and age, and positively related to expense ratio and portfolio turnover.

III. Empirical Results

A. Fund characteristics associated with lottery holdings

To examine 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 while decile 10 contains funds with the highest lottery holdings. Since funds report their holdings as of fiscal quarter-end rather than calendar quarter-end, following prior literature (Schwarz (2012)), we assume that the number of shares for each stock in a portfolio remains unchanged from the last report date of holdings until new holding information is released.

Table 2 shows cross-sectional averages of various characteristics of the decile 1, 5 and 10 portfolios in the portfolio formation quarter. Panel A shows a significant dispersion in the lottery holdings across funds: funds in the highest MAX^{Hold} decile have an average MAX^{Hold}

value of 7.06% compared to 2.95% for funds in the lowest $\mathrm{MAX}^{\mathrm{Hold}}$ decile.[6] The average size for the lowest $\mathrm{MAX}^{\mathrm{Hold}}$ funds is $2.16 billion, compared with $940 million for the highest $\mathrm{MAX}^{\mathrm{Hold}}$ funds. The average fund in the highest $\mathrm{MAX}^{\mathrm{Hold}}$ decile is about four years younger, charges 0.23% more in expenses per year, and has 49% higher annual turnover compared to the average fund in the lowest $\mathrm{MAX}^{\mathrm{Hold}}$ decile.

Funds with high lottery holdings exhibit different factor loadings compared to their low lottery holdings counterparts. Panel B shows that High $\mathrm{MAX}^{\mathrm{Hold}}$ funds have significantly higher exposures to market (β^{MKT}), small cap (β^{SMB}), and momentum (β^{UMD}) but lower value exposure (β^{HML}) compared to Low $\mathrm{MAX}^{\mathrm{Hold}}$ funds. Funds in the highest MAX decile perform significantly worse than funds in the lowest MAX decile portfolio (average 4-factor quarterly alpha of -1.11% compared to -0.01%). Panel C shows similar results when we examine stock characteristics instead of factor exposures. We find that High $\mathrm{MAX}^{\mathrm{Hold}}$ funds are more likely to hold small cap, growth, and recent winner stocks compared with Low $\mathrm{MAX}^{\mathrm{Hold}}$ funds.

Is the heterogeneity in lottery holdings shown in Panel A simply due to differences in the funds' investment styles? To explore this possibility, we investigate the cross-sectional variation in lottery holdings of funds within each investment style. We classify funds into various investment styles using the Lipper investment categories from the CRSP mutual fund data. 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 but is pervasive across all investment styles. Across all five style, funds in the highest MAX decile have significantly more lottery holdings than funds in the lowest MAX decile, with t-statistics of the high minus low portfolio ranging from 7.50 to 9.85. In sum, the cross-sectional variation in funds' lottery holdings is wide and highly significant across all investment styles and not simply due to differences in investment styles.

[6]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. For example, Panel A shows that on average, the proportion of a fund's stock holdings that is invested in the top quintile of lottery stocks (MAX_PROP) is 5%. Panel B shows large cross-sectional variation in lottery holdings. Specifically, funds in the high MAX_PROP (decile 10) on average invest 16% of their assets in lottery stocks in contrast to only 1% for funds in the low MAX_PROP (decile 1).

B. Lottery holdings and future fund performance

In this section, we investigate the extent to which the lotteryness of a fund's holdings predicts fund performance. Lottery stocks are known to underperform in the future. Investors are willing to pay for a premium for holding such stocks, as a result of which they are overpriced and offer lower expected returns (Bali et al. (2011)). However, implications of holding lottery stocks for future fund performance are not clear ex ante. On one hand, funds hold diversified portfolios that can attenuate the effect of lottery stocks on fund performance. On the other hand, it is likely that lottery features of stocks are not easy to diversify away, and a portfolio of lottery stocks also exhibits lottery-like payoffs (Bali et al. (2017)). Therefore, we examine the cross-sectional relation between lottery holdings and future fund performance in Section A.1 of the Internet Appendix. Using both univariate portfolio sorts and Fama and MacBeth (1973) regressions to control for fund-specific characteristics, we show that more lottery holdings imply lower future fund performance, which is consistent with well-established evidence that lottery stocks are overpriced and earn lower future returns (see, e.g., Barberis and Huang (2008) and Bali et al. (2011)).[7]

IV. Economic Explanations for Holding Lottery Stocks

The detrimental effect of holding lottery stocks on fund performance raises a natural question: why do funds hold lottery stocks, i.e., what are their economic incentives? There are several possible explanations for this behavior. First, fund managers may hold lottery stocks because investors find lottery stocks attractive, and holding such stocks attracts investor flows. Second, it is possible that, like their investors, managers themselves may find lottery stocks attractive. Finally, agency problems in funds encourage risk-shifting behavior where managers increase their risk toward the end of the year. Buying lottery stocks can be one way for managers to

[7]Specifically, Table A.2 of the Internet Appendix shows that funds in the lowest MAX decile generate 4.68% higher risk-adjusted net-of-fee returns per annum than funds in the highest MAX decile, using a univariate portfolio-level analysis. Moreover, Table A.3 shows that funds with more lottery holdings significantly underperform in the future, a finding robust to controlling for a large number of fund characteristics and other predictors of fund performance.

increase their chances of large returns, allowing managers to catch up to or outperform their peers as the year end draws near. In this section, we test these different explanations.

A. Do funds cater to their investors by holding lottery stocks?

We examine whether funds hold lottery stocks to cater to their investors' preferences. To answer this question, we investigate how fund investors react to a fund's lottery stock holdings. Holding lottery stocks may bring additional flows by attracting investors who prefer such stocks (see, e.g., Kumar (2009) and Bailey et al. (2011)). Prior studies document that characteristics of stocks included in mutual fund portfolios can help predict fund performance.[8] Moreover, there is evidence that after controlling for a fund's past performance, fund investors respond to stock holdings in fund portfolios. For example, Frazzini and Lamont (2008) show that retail investors tend to direct "dumb" money into mutual funds that hold growth stocks and withdraw capital from funds holding value stocks, and as a result, earn lower returns. 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 a reporting delay period. 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 (see, e.g., Ippolito (1992), Chevalier and Ellison (1997), and Sirri and Tufano (1998)). Specifically, for each quarter we sort all funds according to their risk-adjusted performance (the FFC 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 $\text{LOW}_{i,t}$ for each fund i is defined as $Min(0.2, \text{RANK}_{i,t})$, while $\text{MID}_{i,t}$ is defined as Min(0.6,

[8] See, for example, Grinblatt and Titman (1989, 1993); Grinblatt et al. (1995); Daniel and Titman (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).

$\text{RANK}_{i,t} - \text{LOW}_{i,t}$). Finally, $\text{HIGH}_{i,t}$ is defined as $\text{RANK}_{i,t} - \text{LOW}_{i,t} - \text{MID}_{i,t}$,

$$\begin{aligned} FLOW_{i,t+1} \;=\;& \lambda_0 + \lambda_1 \cdot LH_{i,t} + \lambda_2 \cdot LOW_{i,t} + \lambda_3 \cdot MID_{i,t} + \lambda_4 \cdot HIGH_{i,t} + \lambda_5 \cdot LOW_{i,t} \times LH_{i,t} \\ & + \lambda_6 \cdot MID_{i,t} \times LH_{i,t} + \lambda_7 \cdot HIGH_{i,t} \times LH_{i,t} + \sum_{k=1}^{K} \lambda_k \cdot FUND\_CONTROLS_{k,t} + \epsilon_{i,t+1}, \end{aligned} \tag{1}$$

where the dependent variable $\text{FLOW}_{i,t+1}$ is the percentage net flow during the subsequent quarter.[9] Our primary variable of interest is $\text{LH}_{i,t}$, lottery holdings during the current quarter. We use three proxies for lottery holdings, MAX^{Hold}, MAX_PROP, and $\text{TOP10\_MAX}^{\text{Hold}}$, defined in Section II.B. As additional controls, we include a fund's maximum daily return (MAX^{Fund}), interactions of MAX^{Fund} and performance, interactions of lottery holdings and performance, natural log of fund's TNA, natural log of age, expense ratio, turnover ratio, natural log of the fund family's TNA, flows across all funds in a given style, and fund volatility (VOL^{Fund}). We measure all controls as of the end of quarter t. To ease the interpretation of results, we standardize all continuous independent variables to z-scores by demeaning them and then dividing by their respective standard deviations. We estimate the model with both time and fund fixed effects, and we cluster standard errors at the fund level.

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 shows that after controlling for funds' past performance, lottery holdings influence flows. Models (1) – (3) present the univariate regression results where the only independent variable is the lottery holdings ($\text{LH}_{i,t}$). The results in model 1 show that funds holding stocks with high MAX values attract more flows. The magnitude is also economically significant: a one standard deviation increase in MAX^{Hold} is associated with a 0.81% increase in fund flows in the following quarter (roughly a 19% increase for the average fund). Similarly, the coefficient on MAX_PROP of 0.80 is statistically and economically significant and indicates that funds

[9] To address the concern that some funds may 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.

with a one standard deviation increase in the proportion of lottery stocks attract 0.80% higher quarterly flows. In model 3, we consider another lottery holding measure, TOP10_MAX$^{\text{Hold}}$, because fund investors are more likely to observe top 10 holdings of funds that are reported frequently on funds' websites and Morningstar. Model 3 yields similar results when we use TOP10_MAX$^{\text{Hold}}$ as our lottery holding measure in place of MAX_PROP. Consistent with greater salience of funds' top 10 holdings for investors' capital allocation decisions, the coefficient on TOP10_MAX$^{\text{Hold}}$ is higher than both the MAX$^{\text{Hold}}$ and MAX_PROP coefficients across all specifications.[10]

In models 4 through 6, we control for a host of fund-level control variables that may affect flows, including the maximum daily fund return (MAX$^{\text{Fund}}$) as in Akbas and Genc (2020). Our primary finding that lottery holdings predict flows remains robust, with statistically significant coefficients ranging from 0.52 to 0.83 for different proxies of lottery holdings. In addition, to investigate whether the effectiveness of past performance in generating flows varies with the lotteryness of the fund (MAX$^{\text{Fund}}$) or, separately, the lotteryness of a fund's holdings (MAX$^{\text{Hold}}$), we interact the performance measures (LOW, MID, and HIGH) with MAX$^{\text{Hold}}$ and MAX$^{\text{Fund}}$. Model 4 in Table 3, Panel A shows that the coefficient on the interaction term (LOW $\times$ MAX$^{\text{Hold}}$) is significantly negative (coeff. $= -2.43$); the coefficient on the interaction term (MID $\times$ MAX$^{\text{Hold}}$) is insignificant (coeff. $= 0.55$), whereas the coefficient on (HIGH $\times$ MAX$^{\text{Hold}}$) is significantly positive (coeff. $= 2.48$). We obtain similar results when we use MAX_PROP and TOP10_MAX$^{\text{Hold}}$ as proxies for lottery holdings. In contrast, none of the coefficients on the interaction terms between fund performance and MAX$^{\text{Fund}}$ are statistically significant.

These results suggest that not only a fund's lottery holdings help it attract more flows unconditionally but also conditional on better performance, it receives even higher flows compared to poor performers. These results also indicate that MAX$^{\text{Fund}}$ does not significantly

[10]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 that due to limited attention and 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 that such stocks attract higher fund flows. In addition, stocks can be covered in the media for many other reasons beyond being lottery stocks, such as firms being involved in mergers.

predict fund flows even after interacting with fund performance (unconditionally, MAX^{Fund} is significant at the 10% level in only one specification, Model 5). Finally, we show that the effect of lottery stocks is not the same as the effect of winner stocks. Following Agarwal et al. (2014), we explicitly control for proportions of winner and loser stocks in funds' portfolios, and our key results remain unchanged.

B. Investor sophistication and lottery preferences

In this section, we investigate whether sophisticated investors respond differently from unsophisticated investors to mutual fund lottery holdings. Prior studies document that investors of direct-sold funds are more sophisticated than investors of broker-sold funds (see, e.g., Del Guercio and Reuter (2013), Chalmers and Reuter (2012), and Barber et al. (2016)). Therefore, we use a fund's distribution channel to proxy for investor sophistication. Following Evans and Fahlenbrach (2012) and Barber et al. (2016), we split our sample into direct-sold versus broker-sold funds. Specifically, we classify a fund as broker-sold if 75% of its assets are in share classes that meet any of the following three criteria: a front-end load, a back-end load, or a 12b-1 fee greater than 25 bps. A fund is direct-sold if 75% of its assets are held in share classes that do not charge front-end load or back-end load or 12b-1 fee.

To test the hypothesis that fund flows respond differently to lottery holdings across the two distribution channels, we re-estimate models 4 through 6 in Panel A of Table 3 separately for direct-sold and broker-sold funds. Panel B of Table 3 reports the results. We find that the flow effect of lottery stock holdings is more pronounced for funds that are broker-sold compared to those that are direct-sold. The differences in coefficients on lottery holdings between broker-sold and direct-sold funds range from 0.24 to 0.49 and are statistically significant. These results are consistent with the notion that relatively unsophisticated investors in broker-sold funds respond more strongly to the lottery holdings compared to their sophisticated peers in direct-sold funds.

C. Further evidence on investors' response to funds' disclosure of lottery holdings

In the previous section, we show that the lottery features of stocks held by mutual funds help attract flows, especially for less sophisticated investors. The underlying assumption behind this mechanism is that fund investors are able to observe funds' holdings or at least part of the holdings (e.g., top 10 holdings). Such a conjecture 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. To determine whether investors respond specifically to funds' disclosure of lottery holdings, we zoom into the period around filing dates on which funds publicly disclose their portfolios and compare flows before and after these dates. We expect to observe higher flows after filing dates for funds with high lottery holdings when these holdings becomes visible to investors. To test this prediction, we use daily flows data from the Trimtabs database.[11] We employ a difference-in-differences (DID) approach. The key assumption behind the application of a DID methodology to our setting 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 an indicator variable for time (i.e., pre or post filing date) and an indicator variable for lotteryness (high or low) in the following regression:

$$\begin{aligned} FLOW_{i,t+1} &= \lambda_0 + \lambda_1 \times I(TREAT_{i,t}) + \lambda_2 \times I(POST_{i,t}) + \lambda_3 \times I(TREAT_{i,t}) \times I(POST_{i,t}) \\ &\quad + \lambda_4 \cdot LOW_{i,t} + \lambda_5 \cdot MID_{i,t} + \lambda_6 \cdot HIGH_{i,t} + \sum_{k=1}^{K} \lambda_k \cdot FUND\_CONTROLS_{k,t} + \epsilon_{i,t+1}, \end{aligned} \tag{2}$$

The dependent variable $\text{FLOW}_{i,t+1}$ is the daily percentage flow for fund i on day $t+1$ from TrimTabs, defined as the ratio of dollar flows to prior day's total net assets. $\text{I(TREAT}_{i,t})$ is an indicator variable equal to one if a fund is in the top 20% of funds on the basis of lottery

[11] Consistent with Kaniel and Parham (2017), we find that the coverage in the Trimtabs database varies from about 6% of fund share classes at the beginning of our sample period (the year 2000) to approximately 25% at the beginning of the year 2018.

holdings and zero if the fund is in the bottom 20%. We use an indicator variable, $\mathrm{I}(\mathrm{POST}_{i,t})$, to track when lottery holdings are publicly disclosed and observable by investors. We examine flows for the six-week period before ($\mathrm{I}(\mathrm{POST}_{i,t}) = 0$) and six-week period after ($\mathrm{I}(\mathrm{POST}_{i,t}) = 1$) the filing dates. $\mathrm{LOW}_{i,t}$, $\mathrm{MID}_{i,t}$, and $\mathrm{HIGH}_{i,t}$ are the bottom 20%, middle 60%, and top 20% performance quintiles for a fund as defined in Sirri and Tufano (1998) and measured over the quarter prior to the portfolio holding disclosure date. Other fund controls include the fund's maximum daily return ($\mathrm{MAX}^{\mathrm{Fund}}$), natural log of assets, natural log of age, expense ratio, turnover ratio, natural log of its family size, and volatility ($\mathrm{VOL}^{\mathrm{Fund}}$) as well as flows across all funds in a given style, all measured as of the end of the month prior to the portfolio disclosure date. We control for fund and time fixed effects, and cluster standard errors at the fund level.

Panel A of Table 4 shows that the coefficient λ_1 is not statistically significant, indicating that there is no difference between the average daily flow for funds during the six-week period before the filing dates, satisfying the parallel trend assumption for DID analysis. However, the coefficient λ_3, which is the variable of interest, is 0.020 and highly significant in the specification that includes all control variables. This suggests that funds with the largest lottery holdings attract 0.020% higher daily flows after the filing dates than funds with the smallest lottery holdings. This finding is also economically meaningful as the average daily flows are 0.013% in our sample.

The TrimTabs dataset relies on voluntary disclosure by mutual funds and therefore has limited coverage of funds compared to the CRSP mutual fund database. To address this potential concern, we repeat the flow analyses based on equation (2) using monthly flows from the CRSP sample. We use one-month periods on either side of the filing month to examine the difference in flows. The results using the CRSP sample (Panel B of Table 4) are similar to those in Panel A that use the Trimtabs data. Again, the coefficient λ_3, is 0.30 and highly significant in the specification with all controls and fixed effects, showing that funds with highest lottery holdings attract 0.30% more monthly flows after the filing month than funds with least lottery holdings. This finding is also economically large as the average monthly flows are 0.56% in the CRSP sample. Overall, the findings in Table 4, combined with those in Table 3, suggest that funds with more lottery holdings attract significantly more flows, especially when fund investors can observe lottery stocks in funds' disclosed portfolios.

D. Cost-benefit analysis of holding lottery stocks

In this section, we conduct back-of-the-envelope calculation of two offsetting effects of holding lottery stocks on fund flows. On one hand, investments in lottery stocks put a drag on future fund performance, which should be associated with lower fund flows. On the other hand, this effect may be offset by higher flows into funds with lottery stocks if investors prefer such stocks and managers cater to investors' preferences. Moreover, the sensitivity of flows to past performance as well as the sensitivity of flows to lottery holdings are the highest for best performing funds. Therefore, both costs and benefits of lottery investments should be higher for funds with better performance. Consequently, we conduct our analyses separately for worst performing funds (LOW), mid-range performers (MID), and best performing funds (HIGH) as defined earlier in Table 3. For each of these fund groups, we then solve for the breakeven level of lottery holdings, MAX^{OPT}, by equating the costs and benefits of lottery investments.

Section A.2 of the Internet Appendix provides the details of the cost-benefit analysis and shows that funds with worst and mid-range performance have stronger incentives to hold lottery stocks because benefits outweigh costs for a smaller threshold of lottery holdings.[12] However, for the best performing funds, incentives to hold lottery stocks are not as strong because in order to attract more flows, these funds need to substantially increase their lottery holdings (about three standard deviations above the average lottery holdings), which may not be feasible.

E. Why do investors respond to lottery holdings?

In attempting to select funds that will deliver lottery-like returns in the future, investors can examine a fund's past returns or a fund's stock holdings. Our results so far suggest that in

[12]Specifically, MAX^{Hold} for the worst and mid-range performance funds is 5.93 and 6.89, respectively, representing 0.72 and 1.14 standard deviation above the average.

making their investment decisions, investors rely more on funds' lottery holdings than on funds' past lottery-like returns. This raises the question whether a fund's lottery holdings contain information that is distinct from that in a fund's past lottery-like returns. To that end, in this section, we investigate the predictive power of MAX^{Hold} and MAX^{Fund} for funds' future lottery-like returns. 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 $\text{MAX}_{i,t+\tau}^{\text{Fund}}$ is the fund's future maximum daily return from month $t+1$ to $t+12$ (i.e., $\tau = 1, 2, ..., 12$). $\text{MAX}_{i,t}^{\text{Hold}}$ is the lottery holdings of fund i in month t. $\text{MAX}_{i,t}^{\text{Fund}}$ is the fund's maximum daily return in month t. Fund controls include alpha, natural log of total net assets, natural log of age, expense ratio, turnover ratio, fund flows, fund family size, 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 shows that funds' lottery holdings (MAX^{Hold}) significantly predict funds' future maximum daily returns for up to twelve months, whereas the predictive power of funds' past maximum daily returns (MAX^{Fund}) is significant only for four months or less. In other words, MAX^{Hold} has a strong and persistent predictive power for a fund's future lottery-like returns, 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}. Collectively, the results in Table 5, Table 3, and Figure 1 suggest that investors respond to funds' lottery holdings because these holdings strongly predict future lottery-like fund returns.[13]

[13] Table A.4 of the Internet Appendix conducts bivariate portfolio sorts of funds' lottery holdings (MAX^{Hold}) and maximum daily returns (MAX^{Fund}). Results show that MAX^{Hold} remains a strong and negative predictor of performance even after controlling for MAX^{Fund} (significant spread of -0.27 between the extreme portfolios of MAX^{Hold}). In contrast, MAX^{Fund} has little predictive power in predicting a fund's future performance after controlling for MAX^{Hold} (insignificant spread of -0.11 between the extreme portfolios of MAX^{Fund}). These results suggest that MAX^{Hold} possesses information not contained in MAX^{Fund}.

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

Our results so far show that mutual fund investors prefer lottery stocks and, particularly, funds that hold lottery stocks, and that this relationship is stronger with respect to less sophisticated fund investors. It is also possible that relatively more sophisticated fund managers themselves prefer lottery stocks. Edelen et al. (2016) show, for example, that institutional investors tend to buy stocks considered to be overvalued. In this section, we attempt to disentangle managers' lottery stock preferences from those of fund investors. For this purpose, we use the manager's ownership interest in the fund or funds they manage.[14] As shown in Ma and Tang (2019), managerial ownership can reduce the convexity of option-like reward structures and weaken managers' agency-driven incentives to take on more risk. If managers do not prefer lottery stocks, we would expect portfolio managers with greater ownership to hold fewer lottery stocks. In contrast, if fund managers prefer lottery stocks, we would expect funds with higher managerial ownership to invest more heavily in such stocks.

To test these competing predictions, we estimate the following Fama-MacBeth regression:

$$LH_{i,t} = \alpha + \beta OWNERSHIP_{i,t-1} + \gamma FUND\_CONTROLS_{i,t-1} + \epsilon_t. \tag{4}$$

Since managerial ownership data is available on an annual basis, we conduct this analysis at the annual level. The dependent variable, $\text{LH}_{i,t}$, is the average fund lottery holdings measured by MAX^{Hold} or $\text{MAX5}^{\text{Hold}}$ of fund i in year t. Following Ma and Tang (2019), we use three measures of managerial ownership, $\text{OWNERSHIP}_{i,t-1}$: OWN_DUM, OWN_RANK, and LN_$OWN. OWN_DUM is an indicator variable that equals one if a portfolio manager has a non-zero stake in a fund, and zero otherwise. OWN_RANK ranks those managers that have a non-zero ownership interest using six separate indicator variables, OWN_RANK_2 to OWN_RANK_7. OWN_RANK_2 is set to one if a manager's ownership interest is from $1-$10,000 and zero otherwise. Similarly, OWN_RANK_3 through OWN_RANK_7 correspond

[14] 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 team member's reported stake in the fund.

to ranges of \$10,001-\$50,000, \$50,001-\$100,000, \$100,001-\$500,000, \$500,001-\$1,000,000, and above \$1,000,000. Finally, our third proxy for ownership, LN_$OWN, is the natural logarithm of the dollar value of managerial ownership. We adopt a piecewise linear specification used for flow-performance regressions as in Sirri and Tufano (1998) to assign uniformly distributed fractional ranks between 0 and 1 to LN_$OWN. This specification allows for changes in the sensitivity of lottery holdings to managerial ownership within three groups: LN_$OWN_LOW, LN_$OWN_MID, and LN_$OWN_HIGH. These LN_$OWN variables represent the bottom 20%, middle 60%, and top 20% dollar ownership, respectively, for fund i in year t.

Table 6 presents the average intercept and slope coefficients from Fama-MacBeth regressions. Model 1 shows that if managers have non-zero stakes in their funds, they are less likely to invest in lottery stocks. In models 2 and 3, we use OWN_RANK and LN_$OWN, respectively, and obtain similar evidence. The coefficients on OWN_RANK_5 through OWN_RANK_7 are significantly negative with the largest coefficient on OWN_RANK_7, indicating that on average, funds with greater manager ownership have smaller lottery holdings. In contrast, coefficients on OWN_RANK_2 through OWN_RANK_4 are insignificant, suggesting that the effect of ownership on lottery holdings is primarily driven by funds with higher ownership.

Model 3 of Table 6 shows significantly negative coefficients on both LN_$OWN_MID and LN_$OWN_HIGH, with the largest coefficient on LN_$OWN_HIGH, confirming that the effect of managerial ownership on lottery holdings is most pronounced among the highest ownership group. In terms of economic significance, model 3 shows that an increase of 10 percentile (say from the 85th to the 95th percentile) in the LN_$OWN_HIGH group is associated with significantly smaller lottery holdings (i.e., 1.68% lower MAX^{Hold}) than a similar move in the LN_$OWN_LOW group (0.02% lower MAX^{Hold}) or LN_$OWN_MID group (0.31% lower MAX^{Hold}). Finally, we draw similar inferences from models 4 through 6, where the dependent variable is $\text{MAX5}^{\text{Hold}}$. Overall, these findings show that managers avoid investing in lottery stocks if they have a larger financial interest in their funds. Moreover, managers' aversion to lottery stocks increases nonlinearly with ownership, resulting in much lower lottery holdings at higher levels of ownership. 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.

G. Risk-shifting behavior through lottery investments

In this section, we test the conjecture 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 convex flow-performance relation suggests that many investors evaluate funds on a calendar-year basis, which may incentivize funds performing poorly earlier in a year to invest in lottery stocks later in the year. Second, buying lottery stocks can be a way for managers to improve their chances of beating their peers prior to year-ends. Based on these arguments, we expect seasonality in funds' holding of lottery stocks if funds resort to risk-shifting behavior.

For each fund i, changes in shares of lottery holdings between quarter t and $t+1$ 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 capture active decisions by managers rather than changes driven by stock prices.

To examine seasonality in lottery holdings, Figure 2 presents the changes in shares of lottery stocks (ΔMAX) held by the funds in the second (Panel A), third (Panel B), and fourth quarter (Panel C). To the extent that the purchases of lottery stocks are likely to occur more towards the end of the year, Panel A serves as a placebo test for seasonality. 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 (Quintile

1) and BEST_PERF represents the top 20% of funds (Quintile 5). Panel A shows that none of the five performance deciles exhibit statistically significant changes in their second quarter lottery holdings. However, the results are sharply 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 quarter based on funds' performance in the first half of year. Panel B shows that the worst performers in the first half of the year significantly increase their lottery investments in the third quarter, while the best performers show an insignificant decrease. Moreover, the relation between lottery holdings and past fund performance decreases monotonically from worst performers to best performers. We observe similar patterns for the fourth quarter when we sort funds based on their performance in the first three quarters. Funds with the worst performance in the first three quarters increase their lottery holdings the most during the last calendar quarter.

We conduct regression analyses to more formally verify seasonality in lottery holdings. Table 7 reports average slope coefficients and R-squares from Fama-MacBeth regressions using changes in funds' lottery holdings (ΔMAX) as the dependent variable. 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 RET_RANK. ADJ_RET is the difference between a fund's performance and the median fund performance, where fund performance is the quarterly alpha from the FFC 4-factor model estimated using fund's daily returns within a quarter. RET_RANK is the percentile return rank of a fund. We measure both ADJ_RET and RET_RANK up to the beginning quarter of the dependent variable.[15]

The first two columns of Table 7 report results for the second calendar quarter. Results show that past relative performance, as measured by ADJ_RET and RET_RANK over the first quarter, does not predict changes in shares of lottery stocks in the next quarter. In contrast, models 3 and 4 show that past relative performance over the first half of the year is negatively related to changes in lottery holdings in the third quarter. The coefficients

[15] For example, if the dependent variable, ΔMAX, is measured in the third quarter, we use ADJ_RET and RET_RANK measured through the first two quarters of the same year. Likewise, for ΔMAX measured in the fourth quarter, we measure ADJ_RET and RET_RANK over the first three quarters.

on ADJ_RET and RET_RANK of −0.004 (t-stat. = −3.22) and −0.003 (t-stat. = −3.08), respectively, indicate that funds with poor performance in the first half of year are more likely to increase their lottery stock investments during the third quarter compared to best performing funds. Similarly, models 5 and 6 show that funds performing poorly in the first three quarters increase their lottery holdings in the last quarter. The coefficients on ADJ_RET and RET_RANK are significantly negative: −0.012 (t-stat. = −3.42) and −0.013 (t-stat. = −3.51), respectively. Overall, this evidence is 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 to catch up to or beat their peers by year end.

V. Asset pricing implications of lottery stock holdings

A number of studies investigate how aggregate institutional trading influences asset prices. Gompers and Metrick (2001), for example, argue that shifts in institutional demand curves and institutional investors' historical preference for large capitalization stocks explain the disappearance of the small firm effect. Several studies also show positive correlations between contemporaneous aggregate changes in institutional ownership and stock returns (see, e.g., Nofsinger and Sias (1999), Wermers (1999, 2000), Parrino et al. (2003)). Motivated by these studies, we provide new cross-sectional evidence showing that overpricing of lottery stocks is related to changes in institutional demand. We then examine mutual funds' lottery holdings and provide time-series evidence to show that the aggregate lottery stock holdings of funds contribute to the lottery premium.

A. Cross-sectional evidence on the lottery premium and changes in institutional ownership

We use the measure in Bennett et al. (2003) and Sias et al. (2006) to proxy for net institutional demand. Specifically, we compute the quarterly percentage change in the number of institutional investors for each firm (ΔINST) using the quarterly 13F institutional ownership data:[16]

$$\Delta INST_{i,t} = \frac{\#\ INST_{i,t} - \#\ INST_{i,t-1}}{\#\ INST_{i,t-1}} \tag{6}$$

where $\#INST_{i,t}$ and $\#INST_{i,t-1}$ is the number of institutional investors holding stock i in quarter t and $t-1$, respectively.

To examine the interaction between the performance of lottery stocks and changes in institutional ownership, we conduct bivariate portfolio analyses. At the end of each quarter, we first sort stocks into quintiles based on ΔINST. Within each quintile, we sort stocks based on the proxy for their lottery feature, maximum daily returns (MAX). Each of the resulting 25 portfolios is value-weighted using market capitalization at the end of the quarter and is held for the next three months and then rebalanced. Motivated by prior findings that retail investors in particular have strong preferences for lottery stocks (see, e.g., Kumar (2009) and Han and Kumar (2013)), we posit that a decrease in ΔINST should be associated with stronger underperformance of lottery stocks, consistent with more institutions selling lottery stocks and more buying from retail investors.

Table 8 reports average excess returns and Fama and French (2015) 5-factor alphas for bivariate portfolios sorted on ΔINST and MAX. Panel A shows that on average, the return spread between high-MAX and low-MAX quintiles is economically and statistically significant in the bottom three quintiles of ΔINST, ranging from −0.73% to −1.25% per month. In contrast, among the top two quintiles of ΔINST, the return spread is insignificant. We obtain similar results with the Fama and French (2015) 5-factor alpha in Panel B. Again, the bottom three quintiles of ΔINST show significant alpha spreads ranging from −0.70% and −1.13% while the alpha spread is insignificant for the top two quintiles of ΔINST. These results indicate that the underperformance of lottery stocks is more pronounced when there is more selling by institutions (i.e., more retail buying), which contributes to greater overpricing of lottery stocks.[17]

[16] Chen, Hong and Stein (2002) and Lehavy and Sloan (2008) employ a similar measure and examine its relation to the cross section of stock returns.

[17] Panel B of Table 8 shows that the 5-factor alphas for the high-MAX quintile within the three lowest ΔINST group is −1.03% (t-stat. = −5.19), −0.77% (t-stat. = −4.93), and −0.75% (t-stat. = −4.76), respectively,

B. Time-series evidence on the lottery premium and aggregate lottery holdings

Flows to mutual funds have been shown to create distortions in capital allocation across stocks as managers increase positions in existing stock holdings. This can contribute to price pressure on stocks held by funds (see, e.g., Coval and Stafford (2007) and Akbas et al. (2015)). Motivated by these findings, we hypothesize that the resulting price pressure contributes to overvaluation. Our results support this hypothesis.

We use the lottery demand factor return in Bali et al. (2017) in our main test, which captures the returns associated with lottery demand.[18] We use a predictive regression where the dependent variable is the one-quarter-ahead lottery demand factor (FMAX) and the key independent variable is the lagged aggregate lottery holding of mutual funds. Since we do not require daily fund returns to investigate asset pricing implications of lottery stock holdings, we extend the sample period back to 1980 when fund holdings data first became available. Although using a longer sample period lends greater statistical power to our asset pricing tests, the results are similar to those for the shorter sample period from 2000 to 2018.

Our empirical prediction is that if funds' holdings of lottery stocks (i.e., lottery demand) contribute to these stocks' overpricing, higher lottery holdings should imply more pronounced future underperformance of lottery stocks, i.e., a more negative FMAX factor return. To test this prediction, we construct an aggregate measure of funds' lottery holdings, $\mathrm{LTY}^{\mathrm{Holding}}$, as the value-weighted average for each of the three proxies: $\mathrm{MAX}^{\mathrm{Hold}}$, MAX_PROP, and $\mathrm{TOP10\_MAX}^{\mathrm{Hold}}$, defined earlier in Section II. We then estimate predictive regression of the lottery demand factor, FMAX, on lagged aggregate lottery holdings:

$$FMAX_t = a + b \cdot LTY_{t-1}^{Holding} + u_t, \tag{7}$$

confirming that the alpha spread is mainly driven by the underperformance of the high-MAX quintile rather than the outperformance of the low-MAX quintile.

[18] Specifically, Bali et al. (2017) construct the lottery-demand factor, FMAX, using the factor-mimicking approach pioneered by Fama and French (1993). We first construct six portfolios through independent sorts on market capitalization (2 groups using NYSE breakpoints) and MAX (3 groups in ascending order).The FMAX factor return in month t is the difference between the average return of the two high-MAX portfolios and two low-MAX portfolios.

We also control for the returns on the three Fama and French factors (MKT, SMB, and HML), Carhart (1997) momentum factor (UMD), and the Pastor and Stambaugh (2003) liquidity factor (LIQ) to investigate the ability of lottery holdings to predict benchmark-adjusted returns,

$$FMAX_{i,t} = a + b \cdot LTY_{t-1}^{Holding} + cMKT_t + dSMB_t + eHML_t + fUMD_t + gLIQ_t + u_t. \quad (8)$$

Panel A of Table 9 reports results from the regression in equation (7). The coefficient on aggregate lottery holdings is significantly negative for each of the three lottery holding measures, indicating that the FMAX factor return is more negative when funds invest more in lottery stocks in aggregate. Panel B reports the results from the multivariate regression in equation (8). Again, the coefficients on funds' aggregate lottery holdings are always negative and significant, suggesting a more pronounced subsequent underperformance of lottery stocks when funds invest more in such stocks. Overall, results in Table 9 show that aggregate lottery holdings of mutual funds contribute to the lottery premium.

VI. Conclusion

Recent studies find that mutual fund investors seek out extreme fund returns, consistent with the notion that fund investors overweight the probability of high payoff states in past return distributions. Motivated by these findings, we examine how fund managers might exploit this behavior by investing in lottery stocks that are expected to offer the desired return characteristics.

We find that managers with high dollar ownership tend to avoid lottery stocks, suggesting that managers themselves do not prefer such stocks. However, funds with more lottery holdings attract larger flows, which is consistent with managers catering to investors' preferences for lottery stocks. Funds bear costs of worse future performance when they invest more in lottery stocks. Our cost-benefit analysis shows that funds with worst and mid-range performance have stronger incentives to invest in lottery stocks because benefits outweigh costs at a smaller threshold of lottery holdings.

Compared to lottery-like fund returns, lottery holdings significantly predict funds' future lottery-like returns over a longer period. In addition, we uncover strong seasonality in lottery holdings. Funds performing poorly earlier in the year significantly increase their investments in lottery stocks later in the year. This finding is consistent with fund managers engaging in risk-shifting behavior by investing more in lottery stocks towards year-ends to catch up to or beat their peers before the year-end. Finally, we find that a decrease in institutional demand for lottery stocks is associated with stronger underperformance of these stocks. We also show that higher aggregate mutual fund lottery holdings imply a more negative lottery demand factor return and contribute to the overpricing of lottery stocks.

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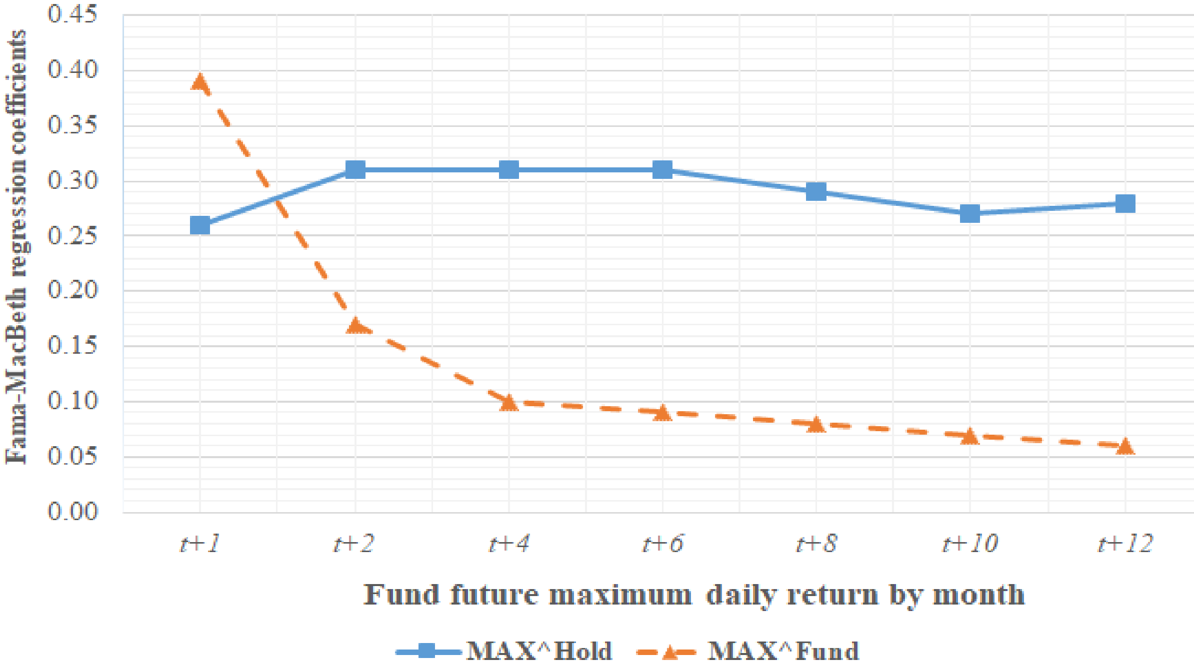
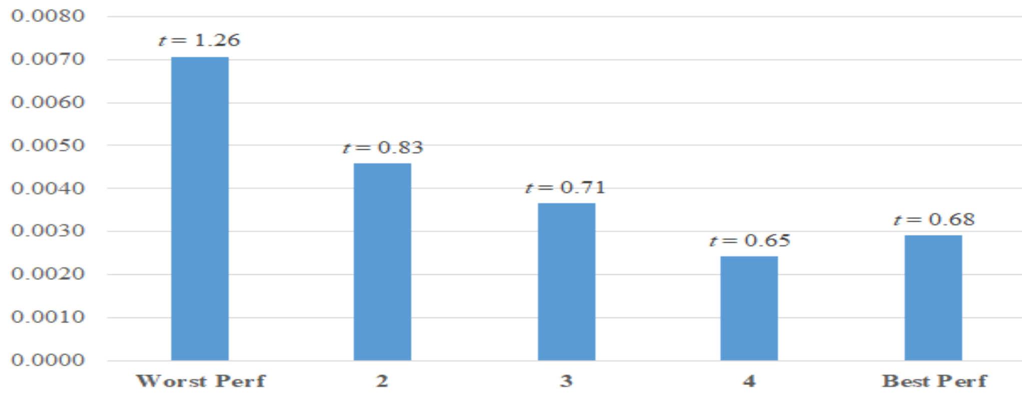
Figure 1: **How long does $\mathrm{MAX}^{\mathrm{Hold}}$ or $\mathrm{MAX}^{\mathrm{Fund}}$ persist as a predictor of future fund maximum daily returns?**



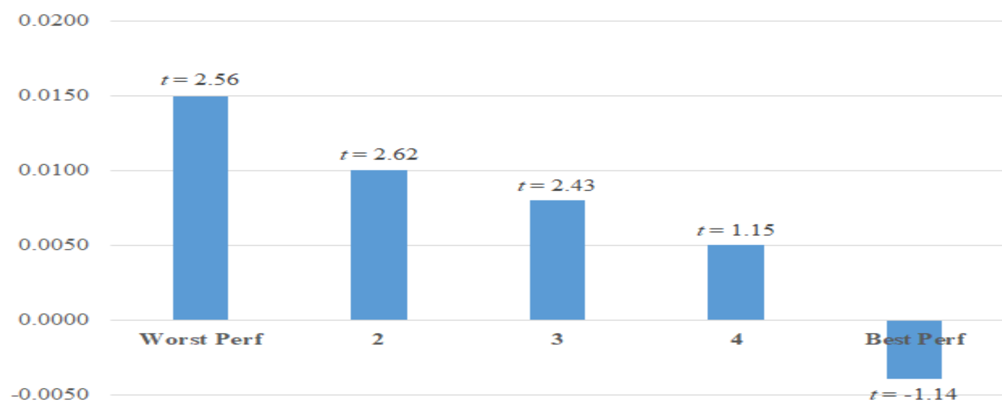
This figure shows the Fama-MacBeth cross-sectional regression coefficients on the lagged $\mathrm{MAX}^{\mathrm{Hold}}$ (the solid line) and $\mathrm{MAX}^{\mathrm{Fund}}$ (the dashed line) in month t. The dependent variable is the future fund maximum daily returns ($\mathrm{MAX}^{\mathrm{Fund}}$) from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

Figure 2: Seasonality in lottery holdings

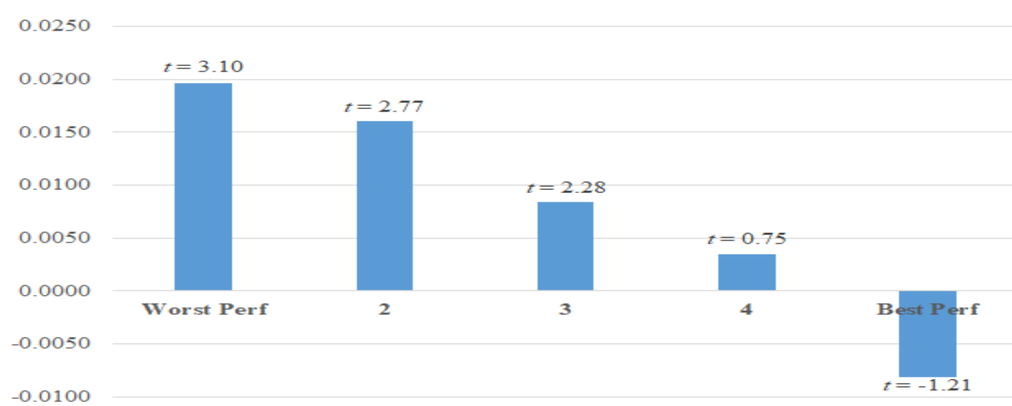
Panel A: Average changes in funds' lottery holdings (ΔMAX) in the 2nd quarter



Panel B: Average changes in funds' lottery holdings (ΔMAX) in the 3rd quarter



Panel C: Average changes in funds' lottery holdings (ΔMAX) in the 4th quarter



This figure presents the changes in funds' lottery holdings (ΔMAX) in the second (Panel A), third (Panel B), and fourth quarter (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. 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. 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-statistics are estimated based on the time-series of changes in funds' lottery holdings in each quintile.

Table 1: Descriptive summary statistics and correlation coefficients

This table reports summary statistics and correlation coefficients of key variables used in the empirical analysis from January 2000 to February 2018. $\mathrm{MAX}^{\mathrm{Hold}}$ is the holding-weighted lottery characteristics using stocks' maximum daily returns within the current month, based on a fund's most recent portfolio holdings. $\mathrm{MAX5}^{\mathrm{Hold}}$ 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 (FFC) four-factor model using a fund's daily returns. TNA ($million) is the total net assets under management at the end of the quarter. Turnover is the annual turnover ratio and expense is the annual expense ratio. Turnover and expense ratio are TNA-weighted averages across all fund share classes. Fund age is the number of years since inception of the oldest share class in the fund. Flow is the quarterly percentage flow.

Variable	N	Mean	Median	Q1	Q3
Panel A: Quarterly lottery holding measures (%)					
$\mathrm{MAX}^{\mathrm{Hold}}$	166,578	4.30	3.65	2.86	4.91
$\mathrm{MAX5}^{\mathrm{Hold}}$	161,459	2.56	2.18	1.74	2.89
Panel B: Other variables					
Alpha (%)	207,388	-0.38	-0.20	-1.79	1.27
TNA ($ million)	207,750	1,471.45	284.40	87.70	979.20
Age (year)	207,750	12.98	10.00	5.42	16.58
Expense (%)	194,714	1.14	1.12	0.82	1.43
Turnover (%)	194,714	92.51	55.00	27.00	101.00
Flow (%)	207,075	3.23	-0.79	-4.18	4.42

Panel C: Correlations

	$\mathrm{MAX}^{\mathrm{Hold}}$	$\mathrm{MAX5}^{\mathrm{Hold}}$	Alpha	TNA	Age	Expense	Turnover	Flow
$\mathrm{MAX}^{\mathrm{Hold}}$	1							
$\mathrm{MAX5}^{\mathrm{Hold}}$	0.87	1						
Alpha	-0.05	-0.05	1					
TNA	-0.05	-0.05	0.02	1				
Age	-0.07	-0.06	-0.01	0.39	1			
Expense	0.16	0.17	-0.03	-0.32	-0.05	1		
Turnover	0.21	0.25	-0.02	-0.19	-0.04	0.35	1	
Flow	0.01	0.01	0.17	-0.07	-0.30	-0.08	-0.06	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 during a month. Other variables are defined in Table 1. Panel B shows the factor exposures and fund alpha, all based on the FFC four-factor using fund daily returns during the portfolio formation quarter. Panel C shows holding-weighted stock characteristics including size ($million), book-to-market (BM), and past six-month cumulative stock returns in percentage (MOM). Panel D shows the heterogeneity of lottery holdings within different investment style. The last row of each panel reports the t-statistics for the difference-in-means test.

Panel A: Fund characteristics

Portfolio	MAX^{Hold}	Assets (millions)	Age (year)	Expense ratio (%)	Turnover
Low MAX^{Hold}	2.95	2158.46	14.99	1.07	0.65
5	3.91	2152.59	14.37	1.14	0.85
High MAX^{Hold}	7.06	940.36	11.30	1.31	1.14
Difference	4.11	-1218.09	-3.70	0.23	0.49
t-stat	(10.78)	(-11.49)	(-8.05)	(10.42)	(7.69)

Panel B: Fund factor exposures and alpha

	β^{MKT}	β^{SMB}	β^{HML}	β^{UMD}	Alpha (%)
Low MAX^{Hold}	0.82	-0.07	0.08	-0.02	-0.01
5	0.90	0.04	0.01	0.01	-0.35
High MAX^{Hold}	0.91	0.55	0.02	0.03	-1.11
Difference	0.09	0.62	-0.06	0.05	-1.10
t-stat	(-2.64)	(26.25)	(-2.41)	(2.13)	(-2.64)

Table 2. (Continued)

Panel C: Holding-weighted stock characteristics

	Size	BM	MOM
Low MAX^{Hold}	10.34	0.39	7.10
5	9.87	0.34	9.03
High MAX^{Hold}	7.49	0.36	17.41
Difference	-2.85	-0.03	10.31
t-stat	(-20.85)	(-2.08)	(2.33)

Panel D: Lottery holdings across different investment styles

	Mid-cap	Small-cap	Micro-cap	Growth	Growth and Income
Low MAX^{Hold}	3.50	4.05	5.07	3.08	3.23
5	4.44	5.21	6.41	3.76	3.82
High MAX^{Hold}	6.24	7.21	8.82	5.84	5.32
Difference	2.75	3.16	3.74	2.76	2.08
t-stat	(7.50)	(8.08)	(9.85)	(9.38)	(8.97)

Table 3: Fund lottery holdings and fund flows

This table reports the results of following panel regression:

$$\begin{aligned} FLOW_{i,t+1} &= \lambda_0 + \lambda_1 \cdot LH_{i,t} + \lambda_2 \cdot LOW_{i,t} + \lambda_3 \cdot MID_{i,t} + \lambda_4 \cdot HIGH_{i,t} + \lambda_5 \cdot LOW_{i,t} \times LH_{i,t} \\ &\quad + \lambda_6 \cdot MID_{i,t} \times LH_{i,t} + \lambda_7 \cdot HIGH_{i,t} \times LH_{i,t} + \sum_{k=1}^{K} \lambda_k \cdot FUND\_CONTROLS_{k,t} + \epsilon_{i,t+1}, \end{aligned}$$

In Panel A, the dependent variable is the quarterly percentage net flow during the subsequent quarter. Three proxies for lottery holdings ($\mathrm{LH}_{i,t}$) are $\mathrm{MAX}^{\mathrm{Hold}}$, MAX_PROP, and TOP10_$\mathrm{MAX}^{\mathrm{Hold}}$. $\mathrm{MAX}^{\mathrm{Hold}}$ is the average monthly $\mathrm{MAX}^{\mathrm{Hold}}$ during a quarter. MAX_PROP is average monthly proportion of fund's stock holdings that is invested in the top quintile of lottery stocks during a quarter. TOP10_$\mathrm{MAX}^{\mathrm{Hold}}$ 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, MID, and HIGH are the bottom 20%, middle 60%, and top 20% performance quintiles for a fund in quarter t as defined in Sirri and Tufano (1998). $\mathrm{RANK}_{i,t}$ is the fractional rank of a fund between 0 (worst performance) and 1 (best performance) where performance is the risk-adjusted performance (the FFC four-factor alpha). The variable $\mathrm{LOW}_{i,t}$ for each fund i is defined as $Min(0.2, \mathrm{RANK}_{i,t})$, $\mathrm{MID}_{i,t}$ is defined as $Min(0.6, \mathrm{RANK}_{i,t} - \mathrm{LOW}_{i,t})$, and $\mathrm{HIGH}_{i,t}$ is defined as $\mathrm{RANK}_{i,t} - \mathrm{LOW}_{i,t} - \mathrm{MID}_{i,t}$. Other fund controls include a fund's maximum daily return ($\mathrm{MAX}^{\mathrm{Fund}}$), interaction of $\mathrm{MAX}^{\mathrm{Fund}}$ and performance, natural log of total net assets (LN_TNA), natural log of age (LN_AGE), expense ratio (EXPENSE), turnover ratio (TURNOVER), natural log of fund family's size (FAMILY_TNA), flows across all funds in a given style (STYLE_FLOW), and fund volatility ($\mathrm{VOL}^{\mathrm{Fund}}$), all measured as of the end of quarter t. LOSER_PROP (WINNER_PROP) is the proportion of the fund's stock holdings invested in the first (fifth) quintile of stocks sorted in ascending order according to their returns over the past six 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 analyzes the impact of a fund's distribution channel on the relation between fund flows and fund's lottery holdings. A fund is classified as broker-sold if 75% of its assets are in share classes that meet any of the following three criteria: a front-end load, a back-end load, or a 12b-1 fee greater than 25 bps. A fund is classified as direct-sold if 75% of its assets are held in share classes that do not charge front-end load or back-end load or 12b-1 fee. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3. (Continued)

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

Variables	1	2	3	4	5	6
MAX^{Hold}	0.809***			0.531***		
	(5.37)			(4.77)		
MAX_PROP		0.799***			0.522***	
		(8.07)			(4.34)	
TOP10_MAX^{Hold}			1.029***			0.826***
			(8.54)			(2.94)
LOW				10.730***	10.820***	10.699***
				(8.80)	(8.82)	(8.75)
MID				1.014***	1.036***	1.056***
				(4.13)	(4.23)	(4.33)
HIGH				12.773***	12.198***	12.568***
				(9.08)	(8.54)	(8.95)
MAX^{Fund}				0.281	0.433*	0.293
				(1.06)	(1.78)	(1.14)
LOW × MAX^{Fund}				-0.849	-2.082	-0.710
				(-0.57)	(-1.69)	(-0.51)
MID × MAX^{Fund}				-0.436	-0.130	-0.490
				(-1.12)	(-0.40)	(-1.36)
HIGH × MAX^{Fund}				1.364	2.008	1.188
				(0.69)	(1.13)	(0.63)
LOW × MAX^{Hold}				-2.432*		
				(-1.92)		
MID × MAX^{Hold}				0.548		
				(1.46)		
HIGH × MAX^{Hold}				2.475**		
				(2.48)		
LOW × MAX_PROP					-1.341*	
					(-1.86)	
MID × MAX_PROP					0.212	
					(0.71)	
HIGH × MAX_PROP					2.906**	
					(2.28)	
LOW × TOP10_MAX^{Hold}						-2.990*
						(-1.84)
MID × TOP10_MAX^{Hold}						0.715**
						(2.09)
HIGH × TOP10_MAX^{Hold}						3.155**
						(2.11)
LN_TNA				-6.610***	-6.602***	-6.582***
				(-21.57)	(-21.54)	(-21.49)
LN_AGE				-5.746***	-5.757***	-5.753***
				(-18.82)	(-18.88)	(-18.86)
EXPENSE				-0.253	0.094	0.035
				(-0.07)	(0.03)	(0.01)
TURNOVER				0.242	0.274	0.274
				(0.79)	(0.90)	(0.90)
FAMILY_TNA				2.427***	2.421***	2.423***
				(6.06)	(6.04)	(6.05)
STYLE_FLOW				0.464***	0.490***	0.477***
				(4.78)	(5.04)	(4.92)
VOL^{Fund}				-0.180	0.031	0.073
				(-0.64)	(0.11)	(0.26)
LOSER_PROP				-0.194**	-0.182**	-0.148*
				(-2.55)	(-2.39)	(-1.93)
WINNER_PROP				1.377***	1.360***	1.400***
				(16.07)	(15.84)	(16.27)
INTERCEPT	8.231***	9.377***	7.943***	-0.635	0.975	0.143
	(11.23)	(13.47)	(11.32)	(-0.83)	(1.29)	(0.19)
Fund/Time fixed effects	Y/Y	Y/Y	Y/Y	Y/Y	Y/Y	Y/Y
Observations	147,140	142,634	142,640	132,662	132,642	132,643
Adjusted R^2	0.037	0.038	0.038	0.095	0.097	0.099

Table 3. (Continued)

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

	1	2	3	4	5	6
	Broker-sold			Direct-sold		
MAX^{Hold}	0.861***			0.413**		
	(4.18)			(2.30)		
MAX_PROP		0.641***			0.403***	
		(2.63)			(2.97)	
$\text{TOP10\_MAX}^{\text{Hold}}$			1.121***			0.627**
			(3.07)			(2.65)
Diff. in coef. (Broker-sold − Direct-sold)	0.448***	0.238**	0.494***			
p-value	(0.01)	(0.03)	(0.01)			
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	51,791	51,784	51,784	80,871	80,858	80,859
Adjusted R^2	0.097	0.096	0.097	0.070	0.070	0.070

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 panel regression:

$$FLOW_{i,t+1} = \lambda_0 + \lambda_1 \times I(TREAT_{i,t}) + \lambda_2 \times I(POST_{i,t}) + \lambda_3 \times I(TREAT_{i,t}) \times I(POST_{i,t}) + \lambda_4 \cdot LOW_{i,t} + \lambda_5 \cdot MID_{i,t} + \lambda_6 \cdot HIGH_{i,t} + \sum_{k=1}^{K} \lambda_k \cdot FUND\_CONTROLS_{k,t} + \epsilon_{i,t+1},$$

The dependent variable $\text{FLOW}_{i,t+1}$ is the daily percentage flow for fund i on day $t+1$ from TrimTabs, defined as the ratio of dollar flows to prior day's total net assets. $\text{I(TREAT}_{i,t})$ is an indicator variable equal to one if the fund is in the top 20% of funds on the basis of lottery holdings and zero if the fund is in the bottom 20%. $\text{I(POST}_{i,t})$ is an indicator variable that tracks when lottery holdings are publicly disclosed and observable by investors. Flows are examined for the six-week period before ($\text{I(POST}_{i,t}) = 0$) and six-week period after ($\text{I(POST}_{i,t}) = 1$) the filing dates. $\text{LOW}_{i,t}$, $\text{MID}_{i,t}$, and $\text{HIGH}_{i,t}$ are the bottom 20%, middle 60%, and top 20% performance quintiles for a fund as defined in Sirri and Tufano (1998) and measured over the quarter prior to the portfolio holding disclosure date. Other fund controls include the fund's maximum daily return (MAX^{Fund}), natural log of assets, natural log of age, expense ratio, turnover ratio, natural log of its family size, and volatility (VOL^{Fund}) as well as flows across all funds in a given style, all measured as of the end of the month prior to the portfolio disclosure date. Fund and time fixed effects are included, and standard errors are clustered at the fund level. λ_3 is the parameter of interest (i.e., the DID estimator). Panel B repeats similar analyses using monthly flows from the CRSP Survivorship Bias Free Mutual Fund Database that has more comprehensive coverage of funds. We use one-month periods on either side of the filing month to examine the difference in flows. *, **, 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

λ_1: I(TREAT)	-0.012	0.016	Avg. daily flow of treatment group in pre-treatment period
	(-0.85)	(1.37)	less avg. daily flow of control group in pre-treatment period
λ_2: I(POST)	0.007	0.008	Avg daily flow of control group in post-treatment period less
	(0.99)	(1.05)	avg. daily flow of control group in pre-treatment period
λ_3: I(TREAT) × I(POST)	0.022***	0.020***	DID estimate
	(3.77)	(3.51)	
Fund controls	Yes	Yes	
Fund/Time fixed effects	No	Yes	
# of daily observations	885,277	885,277	
# of unique funds	2,161	2,161	
Adjusted R^2	0.098	0.132	

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

λ_1: I(TREAT)	-0.134	0.172	Avg. monthly flow of treatment group in pre-treatment period
	(-1.44)	(1.14)	less avg. monthly flow of control group in pre-treatment period
λ_2: I(POST)	-0.127	-0.079	Avg monthly flow of control group in post-treatment period less
	(-1.09)	(-0.65)	avg. monthly flow of control group in pre-treatment period
λ_3: I(TREAT) × I(POST)	0.390***	0.297**	DID estimate
	(2.89)	(2.52)	
Fund controls	Yes	Yes	
Fund/Time fixed effects	No	Yes	
# of monthly observations	138,129	138,129	
# of unique funds	4,186	4,186	
Adjusted R^2	0.133	0.196	

Table 5: $\mathbf{MAX^{Hold}}$ versus $\mathbf{MAX^{Fund}}$ as predictor of funds' future maximum daily returns

The table shows the coefficients on lagged $\mathrm{MAX^{Hold}}$ and $\mathrm{MAX^{Fund}}$ from the following Fama-MacBeth cross-sectional regressions:

$$MAX_{i,t+\tau}^{Fund} = \lambda_{0,t} + \lambda_{1,t} \cdot MAX_{i,t}^{Hold} + \lambda_{2,t} \cdot MAX_{i,t}^{Fund} + \sum_{k=1}^{K} \lambda_{k,t} \cdot FUND\_CONTROLS_{k,t} + \varepsilon_{i,t+1}.$$

The dependent variable is the future fund maximum daily returns from month $t+1$ to $t+12$. $\mathrm{MAX^{Hold}}$ is the holding-weighted lottery characteristics using maximum daily returns of stocks within the current month, based on a fund's most recent portfolio holdings. $\mathrm{MAX^{Fund}}$ is the maximum daily fund return within a month. All regressions include fund controls such as the alpha, natural log of total net assets, natural log of age, expense ratio, turnover ratio, fund flows, fund family size, β^{SMB}, β^{HML}, β^{UMD}, return gap, active share, R^2, and fund volatility ($\mathrm{VOL^{Fund}}$), 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.	$\mathrm{MAX}^{\mathrm{Fund}}_{t+1}$	$\mathrm{MAX}^{\mathrm{Fund}}_{t+2}$	$\mathrm{MAX}^{\mathrm{Fund}}_{t+3}$	$\mathrm{MAX}^{\mathrm{Fund}}_{t+4}$	$\mathrm{MAX}^{\mathrm{Fund}}_{t+5}$	$\mathrm{MAX}^{\mathrm{Fund}}_{t+6}$
$\mathrm{MAX}^{\mathrm{Hold}}_{t}$	0.26***	0.41***	0.34***	0.31***	0.34***	0.31***
	(2.84)	(5.39)	(5.18)	(4.99)	(4.96)	(4.65)
$\mathrm{MAX}^{\mathrm{Fund}}_{t}$	0.39***	0.17***	0.09*	0.10*	0.09	0.09
	(3.84)	(3.72)	(1.92)	(1.88)	(1.50)	(1.04)
Fund controls	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.69	0.67	0.65	0.64	0.64	0.60

Coef.	$\mathrm{MAX}^{\mathrm{Fund}}_{t+7}$	$\mathrm{MAX}^{\mathrm{Fund}}_{t+8}$	$\mathrm{MAX}^{\mathrm{Fund}}_{t+9}$	$\mathrm{MAX}^{\mathrm{Fund}}_{t+10}$	$\mathrm{MAX}^{\mathrm{Fund}}_{t+11}$	$\mathrm{MAX}^{\mathrm{Fund}}_{t+12}$
$\mathrm{MAX}^{\mathrm{Hold}}_{t}$	0.29***	0.27***	0.29***	0.27***	0.25***	0.28***
	(4.26)	(3.12)	(4.53)	(3.59)	(3.84)	(3.88)
$\mathrm{MAX}^{\mathrm{Fund}}_{t}$	0.08	0.08	0.05	0.07	0.03	0.06
	(1.06)	(1.17)	(1.11)	(0.97)	(0.67)	(0.48)
Fund controls	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.58	0.56	0.55	0.52	0.52	0.50

Table 6: Fund lottery holdings and portfolio manager ownership

The table reports 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 $t+1$. OWN_DUM is an indicator variable that equals one if a portfolio manager has a non-zero stake in a fund, and zero otherwise. OWN_RANK ranks those managers that have a non-zero ownership interest using six separate indicator variables, OWN_RANK_2 to OWN_RANK_7. OWN_RANK_2 is set to one if a manager's ownership interest is from $1-$10,000 and zero otherwise. Similarly, OWN_RANK_3 through OWN_RANK_7 correspond to ranges of $10,001-$50,000, $50,001-$100,000, $100,001-$500,000, $500,001-$1,000,000, and above $1,000,000. LN_$OWN is the natural logarithm of the dollar value of managerial ownership. A piecewise linear specification is estimated similar to the flow-performance regressions as in Sirri and Tufano (1998) where LN_$OWN is assigned fractional ranks that are uniformly distributed between 0 and 1. This specification allows for changes in the sensitivity of lottery holdings to managerial ownership within three groups: LN_$OWN_LOW, LN_$OWN_MID, and LN_$OWN_HIGH. These LN_$OWN variables represent the bottom 20%, middle 60%, and top 20% dollar ownership, respectively, for fund i in year t. Fund controls include past year performance (PAST_YEAR_PERF), the lagged natural log of total net assets (LN_TNA), natural log of age (LN_AGE), expense ratio (EXPENSE), turnover ratio (TURNOVER), and fund family size (FAMILY_TNA), all measured as of the end of year t. Fund flow is the average quarterly 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 from 2007 to 2014 for which managerial ownership data is available.

	Dep var. = MAX^{Hold}_{t+1}			Dep var. = $MAX5^{Hold}_{t+1}$		
	1	2	3	4	5	6
OWN_DUM	-0.262**			-0.146***		
	(-2.59)			(-2.95)		
OWN_RANK_2		0.036			0.002	
		(0.40)			(0.03)	
OWN_RANK_3		-0.053			-0.024	
		(-1.01)			(-0.85)	
OWN_RANK_4		-0.095			-0.089	
		(-0.76)			(-0.53)	
OWN_RANK_5		-0.245**			-0.121**	
		(-2.55)			(-2.08)	
OWN_RANK_6		-0.276**			-0.250**	
		(-2.67)			(-2.71)	
OWN_RANK_7		-0.343***			-0.297**	
		(-3.06)			(-2.63)	
LN_$OWN_LOW			0.002			0.001
			(0.10)			(0.29)
LN_$OWN_MID			-3.109**			-2.354**
			(-2.08)			(-2.62)
LN_$OWN_HIGH			-16.847***			-14.597***
			(-3.18)			(-2.92)
PAST_YEAR_PERF	0.140	0.242	0.181	0.058	0.105	0.077
	(0.47)	(1.02)	(0.88)	(0.37)	(0.93)	(0.79)
LN_TNA	-0.144**	0.772	0.323	-0.138**	0.378	0.141
	(-2.07)	(1.65)	(0.81)	(-2.31)	(1.49)	(0.63)
LN_AGE	-0.191	-0.451**	-0.551***	-0.069	-0.224*	-0.239**
	(-1.06)	(-2.12)	(-2.85)	(-0.66)	(-2.05)	(-2.34)
EXPENSE	-0.066	-0.138	-0.132	-0.015	-0.049	-0.032
	(-0.13)	(-0.27)	(-0.25)	(-0.06)	(-0.20)	(-0.13)
TURNOVER	-0.086	-0.107	-0.086	-0.050	-0.057	-0.046
	(-1.01)	(-1.31)	(-1.01)	(-1.03)	(-1.20)	(-0.95)
FLOW	-0.019	0.003	0.009	-0.021	-0.001	-0.001
	(-0.77)	(1.09)	(1.41)	(-0.97)	(-1.26)	(-0.09)
FAMILY_TNA	0.013	0.002	-0.071	0.002	-0.007	0.023
	(0.71)	(0.08)	(-1.10)	(0.32)	(-0.44)	(0.92)
Observations	10,994	10,994	10,994	10,994	10,994	10,994
Adj. R^2	0.12	0.15	0.14	0.10	0.12	0.11

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 changes in funds' lottery holdings (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. RET_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 ($\mathrm{MAX}^{\mathrm{Hold}}$) 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					
	(0.39)					
RET_RANK in the 1st qtr		0.001				
		(0.66)				
Avg. ADJ_RET (1st + 2nd)			-0.004***			
			(-3.22)			
Avg. RET_RANK (1st + 2nd)				-0.003**		
				(-3.08)		
Avg. ADJ_RET (1st + 2nd + 3rd)					-0.012***	
					(-3.42)	
Avg. RET_RANK (1st + 2nd +3rd)						-0.013***
						(-3.51)
$\mathrm{MAX}^{\mathrm{Hold}}$ in the 1st qtr	-0.012	-0.011				
	(-1.39)	(-1.20)				
Avg. $\mathrm{MAX}^{\mathrm{Hold}}$ (1st + 2nd)			-0.012	-0.013		
			(-1.11)	(-1.20)		
Avg. $\mathrm{MAX}^{\mathrm{Hold}}$ (1st + 2nd + 3rd)					-0.013	-0.013
					(-1.07)	(-1.06)
Observations	43,675	43,675	42,299	42,299	40,883	40,883
Adj. R^2	0.01	0.01	0.01	0.01	0.01	0.01

Table 8: Bivariate portfolios of stock lottery feature (MAX) and changes in institutional ownership

This table reports average excess returns and Fama-French (2015) 5-factor alphas on bivariate portfolios of individual stocks sorted on changes in the institutional ownership (ΔINST) and the stock-level maximum daily returns (MAX). ΔINST is the quarterly percentage change in the number of institutional investors for each firm, defined as the difference between the number of institutional shareholders at the beginning and end of the quarter, divided by the number of institutional investors at the beginning of the quarter. At the end of each calendar quarter, individual stocks are first sorted into quintiles based on ΔINST, and then within each quintile, stocks are further sorted based on the proxy for the lottery feature (MAX). Each portfolio is value-weighted using stock market capitalization at the end of the quarter as weights and is held for the next three months and then rebalanced. This table also reports the difference in returns for the High MAX and Low MAX portfolio within each ΔINST quintile. Panel A also reports the average ΔINST for each ΔINST quintile. The Fama-French (2015) 5-factor model includes the excess market return (MKTRF), the size factor (SMB), the value factor (HML), the profitability factor (RMW), and the investment factor (CMA). The returns and alphas are in monthly percentage. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate significance of the return difference at the 10%, 5%, and 1% level, respectively. The sample period is from January 1980 to February 2018.

Panel A: Average excess return

	Low MAX	2	3	4	High MAX	High MAX − Low MAX	Average ΔINST
Low ΔINST	0.78***	0.64***	0.44	-0.01	-0.47	-1.25***	-0.57%
	(4.43)	(2.86)	(1.67)	(-0.03)	(-1.02)	(-3.43)	
2	0.84***	0.69***	0.52*	0.43	-0.11	-0.94***	-0.09%
	(4.52)	(3.05)	(1.96)	(1.36)	(-0.30)	(-3.23)	
3	0.67***	0.82***	0.68**	0.42	-0.06	-0.73**	0.03%
	(3.38)	(3.50)	(2.70)	(1.34)	(-0.16)	(-2.25)	
4	0.69***	0.74***	0.72***	0.53	0.28	-0.41	0.20%
	(3.86)	(3.49)	(2.92)	(1.82)	(0.72)	(-1.24)	
High ΔINST	0.60***	0.71***	0.87**	0.87**	0.55	-0.04	0.85%
	(3.15)	(3.29)	(3.32)	(2.57)	(1.30)	(-0.13)	

Panel B: Fama-French (2015) 5-factor alpha

	Low MAX	2	3	4	High MAX	High MAX − Low MAX
Low ΔINST	0.11	-0.08	-0.23	-0.63***	-1.03***	-1.13***
	(1.08)	(-0.52)	(-1.66)	(-3.53)	(-5.19)	(-5.51)
2	0.12	-0.14	-0.49***	-0.48***	-0.77***	-0.89***
	(1.12)	(-1.18)	(-4.03)	(-3.47)	(-4.93)	(-4.49)
3	-0.05	0.11	-0.14	-0.36***	-0.75***	-0.70***
	(-0.43)	(0.86)	(-1.13)	(-2.94)	(-4.76)	(-3.58)
4	-0.02	-0.14	-0.09	-0.25*	-0.26	-0.24
	(-0.13)	(-1.42)	(-0.75)	(-1.83)	(-1.51)	(-1.03)
High ΔINST	-0.04	0.03**	0.28**	0.38**	0.20	0.24
	(-0.51)	(0.39)	(2.04)	(2.28)	(0.96)	(1.01)

Table 9: Lottery holdings and the lottery factor premium

The table reports the results from the predictive regressions of the lottery factor premium on lottery holdings. The dependent variable is the one-quarter-ahead lottery factor premium (FMAX), defined as the value-weighted average return of the high-MAX portfolios minus the average return of the low-MAX portfolios. 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}, MAX_PROP, and $\text{TOP10\_MAX}^{\text{Hold}}$. MAX^{Hold} is the average monthly MAX^{Hold} during a quarter. MAX_PROP is average monthly proportion of fund's stock holdings that is invested in lottery stocks (i.e., stocks whose MAX is in the top quintile among all stocks) during a quarter. $\text{TOP10\_MAX}^{\text{Hold}}$ 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 univariate regressions where the only independent variable is the lottery holding. Panel B reports multivariate regressions controlling for the lagged FMAX factor as well as the contemporaneous FFC four factors augmented with the liquidity risk factor (LIQ) of Pastor and Stambaugh (2003). The sample period is from January 1980 to February 2018. Newey-West adjusted t-statistics are given in parentheses. *, **, and *** indicate significance of the coefficients at the 10%, 5%, and 1% level, respectively.

Panel A: Univariate regression, Dep. Var = FMAX

	MAX^{Hold}	MAX_PROP	$\text{TOP10\_MAX}^{\text{Hold}}$
Coef.	-0.56**	-0.50***	-0.63***
t-stat	(-2.69)	(-2.89)	(-2.98)
Adj. R^2 (%)	5.22	4.86	4.59

Panel B: Multivariate regression, Dep. Var = FMAX

	MAX^{Hold}	MKTRF	SMB	HML	UMD	LIQ	LAG_FMAX
Coef.	-0.55***	0.45***	0.71***	-0.60***	-0.03	-7.24*	0.04
t-stat	(-3.74)	(5.69)	(7.94)	(-4.58)	(-0.35)	(-1.96)	(0.85)
Adj. R^2 (%)	72.53						
	MAX_PROP	MKTRF	SMB	HML	UMD	LIQ	LAG_FMAX
Coef.	-0.63**	0.45***	0.66***	-0.67***	-0.06	-5.86	0.04
t-stat	(-2.78)	(5.67)	(6.77)	(-5.52)	(-0.77)	(-1.45)	(0.79)
Adj. R^2 (%)	70.11						
	$\text{TOP10\_MAX}^{\text{Hold}}$	MKTRF	SMB	HML	UMD	LIQ	LAG_FMAX
Coef.	-0.57***	0.45***	0.70***	-0.60***	-0.03	-7.46*	0.04
t-stat	(-3.52)	(5.69)	(7.72)	(-4.55)	(-0.34)	(-1.96)	(0.97)
Adj. R^2 (%)	70.67						

Why Do Mutual Funds Hold Lottery Stocks?

Internet Appendix

Section A.1 investigates the predictive power of funds' lottery holdings on future fund performance. We first perform a univariate portfolio-level analysis of lottery holdings and its relation with future fund performance. We then estimate 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 back-of-the-envelope calculation of the two offsetting effects of holding lottery stocks on fund flows.

A.1. Lottery Holdings and Future Fund Performance

A. 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 $\text{MAX5}^{\text{Hold}}$). 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 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 FFC alpha (using both net-of-expense and gross returns) of mutual funds sorted on the 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 almost monotonically from 0.08% to -0.31% per month from decile 1 to decile 10. This indicates a monthly average return difference of -0.39% between the high- and low-MAX^{Hold} deciles with a Newey-West t-statistic of -3.75, showing that this negative return spread is both economically and statistically significant. This result also indicates that funds in the lowest MAX decile generate 4.68% 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 $\text{MAX5}^{\text{Hold}}$, the monthly average alpha spread between the high- and low-MAX^{Hold} deciles is even larger, -0.51% per month (t-stat. = -3.93). 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 of low-MAX^{Hold} funds, underperformance of 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, 4-factor alphas of funds in decile 10 (high-MAX^{Hold} funds) are significantly negative, whereas 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 of high-MAX^{Hold} funds.

B. Fama-MacBeth cross-sectional regressions

To the extent that lottery holdings are correlated with a large number of fund characteristics shown in Tables 1 and 2, multivariate cross-sectional regressions 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 $\text{ALPHA}_{i,t+1}$ is the quarterly percentage alpha for fund i in calendar quarter $t+1$ estimated from the FFC four-factor model using the daily returns of fund i. $\text{ALPHA}_{i,t}$ is the alpha in quarter t. $\text{MAX}_{i,t}^{\text{Hold}}$ is the lottery holdings of fund i in quarter t. Following Goldie, Henry, and Kassa

(2019), we define $\text{MAX}_{i,t}^{\text{Fund}}$ as the maximum daily returns of fund i in the last month of quarter t. $\text{FUND\_CONTROLS}_{i,t}$ include the natural log of total net assets (TNA), natural log of fund age, expense ratio, turnover ratio, fund flows, and fund family size, 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 coefficient on MAX^{Hold} alone is -0.38 with a t-statistic of -3.22, implying that a one standard deviation increase in MAX^{Hold} is associated with a 0.38% 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 the fund characteristics is relatively small (0.01% to 0.10% 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, whenever available, 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. Cost-benefit analysis of holding lottery stocks

We conduct back-of-the-envelope calculation of the two offsetting effects of holding lottery stocks on fund flows separately for the Low performance (LOW), Middle performance (MID), and High performance (HIGH) funds defined in Table 3 to account for the nonlinear relation between flows and a fund's past performance. First, we examine LOW funds defined as the bottom 20% of funds based on rankings of quarterly alpha. The benefits of holding lottery stocks to attract more flows is $0.531\% \times \text{MAX}^{\text{OPT}}$, where 0.531 is the coefficient on MAX^{Hold} associated with one-standard-deviation increase in MAX^{Hold}, as shown in Panel A of Table 3 (see Model 4). The costs of holding lottery stocks are associated with two channels. First of all, a one-standard-deviation increase in MAX^{Hold} is associated with a decrease of -0.40% of quarterly alpha (see Model 10) in Table A.3 of the Internet Appendix, which translates to a -0.2 decrease in LOW in terms of fractional performance ranking in Table 3. As a result, outflows due to the negative performance of funds holding lottery stocks is -0.02146.[19] In addition, LOW funds will lose additional flows because of the interaction term: LOW $\times$ MAX^{Hold}, as shown in Model 5 of Table 3, and the magnitude is: $-2.432\% \times \text{MAX}^{\text{OPT}}$. Setting the benefits and costs of holding lottery stocks equal, we solve for MAX^{OPT}, and find it to be equal to 0.72, indicating that LOW funds need to increase their lottery holdings by at least 0.72 standard deviation above the average, in order to have net inflows from holding lottery stocks. Based on summary statistics in Table 1, the average MAX^{Hold} in our sample is 4.30 with a standard deviation of 2.27. That is, worst performing funds need to have a MAX^{Hold} of 5.93 ($= 4.30 + 0.72 \times 2.27$) for benefits of holding lottery stocks to outweigh costs.

Next, we focus on HIGH funds defined as the top 20% of funds based on rankings of quarterly alpha. The benefits of holding lottery stocks to attract more flows is $0.531\% \times \text{MAX}^{\text{OPT}}$, from Panel A of Table 3. At the same time, HIGH funds will attract additional flows because of the interaction term: HIGH $\times$ MAX^{Hold} as shown in Model 5 of Table 3: $2.906\% \times \text{MAX}^{\text{OPT}}$. Note that due to greater sensitivity of flows to fund performance when best performing funds hold lottery stocks, benefits are higher than those for the worst performers. The estimated costs of holding lottery stocks are outflows from the best performing funds due to performance drag on

[19] This is calculated by using 10.73% (coeff. on LOW in Model 4 of Table 3) multiplied by -0.2.

account of lottery holdings, computed as $12.773\% \times -0.8$, where -0.8 is the decrease in HIGH in terms of fractional performance ranking in Table 3. Setting benefits and costs of holding lottery stocks equal, we again solve for MAX^{OPT}, which in this case turns out to be 2.97, indicating that HIGH funds need to increase lottery holdings by about three standard deviations above the average, in order to have net inflows from holding lottery stocks. That is, best performing funds need to have a MAX^{Hold} of 11.04 ($= 4.30 + 2.97 \times 2.27$) for benefits of holding lottery stocks to outweigh the costs. It is interesting to note that even though both costs and benefits of holding lottery stocks are higher for best performing funds, costs are much higher than the benefits. Therefore, these funds need to hold more lottery stocks than worst performers for benefits to outweigh costs.

Finally, we investigate MID funds defined as the middle 60% of funds based on rankings of quarterly alpha. The benefits of holding lottery stocks to attract more flows is still $0.531\% \times \text{MAX}^{\text{OPT}}$. For MID funds, there are two channels through which the costs are incurred of holding lottery stocks. First, there are outflows due to the performance decline associated with holding lottery stocks, $1.014\% \times -0.6 = -0.00608$, where -0.6 is the decrease in MID in terms of fractional performance ranking in Table 3. In addition, MID funds will not lose any additional flows due to incremental sensitivity of flows to these funds' performance conditional on them holding lottery stocks. As shown in MID, the coefficient on MID $\times$ MAX^{Hold} is statistically insignificant. Again, setting the benefits and costs of holding lottery stocks equal, we solve for MAX^{OPT} and find it to be 1.14, indicating that for the MID funds, they need to increase lottery holdings by at least 1.14 standard deviation above the average, in order to have net inflows from holding lottery stocks. That is, middle-of-the-road performers need to have a MAX^{Hold} of 6.89 ($= 4.30 + 1.14 \times 2.27$) for benefits of holding lottery stocks to outweigh the costs. Not surprisingly, these funds need to hold more lottery stocks than the worst performers but less than the best performers to make it worthwhile.

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

This table reports summary statistics for three alternative lottery holding measures. MAX_PROP is average monthly proportion of fund's stock holdings that is invested in lottery stocks (i.e., stocks whose MAX is in the top quintile among all stocks) during a quarter. $\text{TOP10\_MAX}^{\text{Hold}}$ 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. 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, decile portfolios of mutual funds are formed based on their lottery holdings. Decile 1 contains funds with the lowest lottery holdings and decile 10 contains funds with the highest lottery holdings. Results are also presented for the fifth decile of lottery holdings. The last row reports the t-statistic of the difference-in-means test for each lottery holding measure.

Panel A: Quarterly lottery holding measures

Variable	N	Mean	Median	Q1	Q3
MAX_PROP	161,466	0.05	0.03	0.01	0.06
$\text{TOP10\_MAX}^{\text{Hold}}$	161,466	4.11	3.39	2.59	4.79
LTRY	161,210	53.38	50.68	44.42	60.98

Panel B: Fund characteristics

Low MAX_PROP	0.01	Low $\text{TOP10\_MAX}^{\text{Hold}}$	2.55	Low LTRY	38.02
5	0.02	5	3.60	5	48.52
High MAX_PROP	0.16	High $\text{TOP10\_MAX}^{\text{Hold}}$	7.61	High LTRY	77.20
Difference	0.15	Difference	5.06	Difference	39.18
t-stat	26.81	t-stat	11.83	t-stat	33.73

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 the two measures of lottery holdings. At the beginning of each calendar quarter from January 2000 to February 2018, decile portfolios of mutual funds are formed 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 portfolio is rebalanced. The alphas are monthly and reported in 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	2.95	0.08	0.19***	1.88	0.12**	0.22***
		(1.39)	(3.12)		(2.06)	(3.82)
2	3.35	0.02	0.12**	2.09	0.04	0.14**
		(0.28)	(2.18)		(0.69)	(2.50)
3	3.53	0.00	0.10**	2.19	-0.02	0.09**
		(0.03)	(2.61)		(-0.45)	(2.36)
4	3.71	-0.04	0.06	2.28	-0.02	0.07
		(-1.10)	(1.48)		(-0.57)	(1.74)
5	3.91	-0.02	0.08	2.40	-0.03	0.07
		(-0.45)	(1.53)		(-0.65)	(1.41)
6	4.18	-0.02	0.09	2.54	-0.02	0.08
		(-0.33)	(1.49)		(-0.37)	(1.40)
7	4.51	-0.02	0.09	2.73	0.01	0.12*
		(-0.34)	(1.51)		(0.21)	(1.94)
8	4.95	-0.06	0.05	2.96	-0.04	0.07
		(-0.94)	(0.86)		(-0.69)	(1.15)
9	5.54	-0.18***	-0.06	3.28	-0.17**	-0.05
		(-2.90)	(-1.06)		(-2.38)	(-0.71)
High	7.06	-0.31***	-0.20**	3.93	-0.38	-0.27**
		(-3.34)	(-2.16)		(-3.67)	(-2.62)
High − Low	4.11***	-0.39***	-0.38***	2.07***	-0.51***	-0.50***
	(10.78)	(-3.75)	(-3.68)	(8.98)	(-3.93)	(-3.85)

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

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

$$ALPHA_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot ALPHA_{i,t} + \lambda_{2,t} \cdot MAX^{Hold}_{i,t} + \lambda_{3,t} \cdot MAX^{Fund}_{i,t} + \sum_{k=1}^{K} \lambda_{k,t} \cdot FUND\_CONTROLS_{k,t} + \varepsilon_{i,t+1}.$$

The dependent variable is the quarterly percentage alpha for fund i in calendar quarter $t+1$ calculated from the FFC four-factor model using daily returns within a quarter. $\text{ALPHA}_{i,t}$ is alpha in the prior quarter. Fund lottery holdings in this table is measured by MAX^{Hold}, the holding-weighted lottery characteristics using stocks' maximum daily returns within the current month. $\text{MAX}^{\text{Fund}}_{i,t}$ 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 fund family size, all measured as of the end of quarter t. Controls for FFC SMB (size), HML (value), and UMD (momentum) exposures calculated from daily returns during prior quarter, are included. 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}	-0.38***		-0.35***	-0.35***	-0.27**	-0.31***	-0.30***	-0.28***	-0.25**	-0.40***
	(-3.22)		(-3.70)	(-4.70)	(-2.39)	(-3.29)	(-3.70)	(-2.97)	(-2.51)	(-3.09)
MAX^{Fund}		-0.22***	-0.12	-0.18	-0.11	-0.12	-0.10	-0.12	-0.05	-0.18
		(-2.81)	(-1.48)	(-1.52)	(-1.38)	(-1.30)	(-1.21)	(-1.55)	(-0.94)	(-1.25)
ALPHA				0.27***	0.23***	0.25***	0.24***	0.25***	0.23***	0.23***
				(3.77)	(2.76)	(3.35)	(3.59)	(3.74)	(2.94)	(2.92)
LN_TNA				-0.04***						-0.03
				(-2.68)						(-0.93)
LN_AGE				0.02						-0.01
				(1.34)						(-0.68)
EXPENSE				-0.10***						-0.09**
				(-3.58)						(-2.31)
TURNOVER				-0.07**						-0.09**
				(-2.24)						(-2.21)
FLOW				-0.01						-0.01
				(-0.57)						(-0.23)
FAMILY_TNA				0.02						0.02
				(1.17)						(0.67)
β^{SMB}				0.17**						0.24**
				(2.48)						(2.41)
β^{HML}				0.17						0.35**
				(1.43)						(2.26)
β^{UMD}				-0.16*						-0.27**
				(-1.74)						(-2.12)
RETURN_GAP					0.09**				0.10**	0.07**
					(2.09)				(2.24)	(2.10)
ACTIVE_SHARE						0.05			0.14**	0.10*
						(0.93)			(2.31)	(1.73)
R^2							0.09		0.12	0.01
							(1.38)		(1.22)	(0.16)
VOL^{Fund}								-0.04	-0.07	-0.19*
								(-0.46)	(-0.84)	(-1.82)
Fund-quarter obs	163,338	163,338	163,338	163,338	140,949	141,801	161,199	163,338	140,949	140,949
Average R-squared	0.05	0.05	0.08	0.21	0.12	0.13	0.14	0.14	0.18	0.27

Table A.4: Bivariate portfolios of fund lottery holdings ($\mathrm{MAX}^{\mathbf{Hold}}$) and fund maximum daily returns ($\mathrm{MAX}^{\mathbf{Fund}}$)

This table reports the FFC four-factor alphas for bivariate portfolios of mutual funds sorted on fund lottery holdings ($\mathrm{MAX}^{\mathrm{Hold}}$) and fund maximum daily returns ($\mathrm{MAX}^{\mathrm{Fund}}$). In Panel A, for each quarter funds are first sorted into quintiles based on $\mathrm{MAX}^{\mathrm{Fund}}$, and then within each quintile, funds are sorted into decile portfolios based on fund lottery holdings ($\mathrm{MAX}^{\mathrm{Hold}}$) over the previous quarter so that decile 1 (10) contains funds with the lowest (highest) lottery holdings. In Panel B, reverse sequential sort is conducted by first sorting funds into quintiles based on $\mathrm{MAX}^{\mathrm{Hold}}$, and then within each quintile, funds are sorted into decile portfolios based on fund maximum daily returns ($\mathrm{MAX}^{\mathrm{Fund}}$). The alphas are monthly and reported in 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 $\mathrm{MAX}^{\mathrm{Fund}}$ then $\mathrm{MAX}^{\mathrm{Hold}}$

Low $\mathrm{MAX}^{\mathrm{Hold}}$	2	3	4	5	6	7	8	9	High $\mathrm{MAX}^{\mathrm{Hold}}$	High − Low
0.09	0.04	-0.01	-0.03	-0.04	-0.04	-0.04	-0.04	-0.09	-0.18*	-0.27***
(1.55)	(0.80)	(-0.24)	(-0.67)	(-0.82)	(-0.77)	(-0.80)	(-0.63)	(-1.43)	(-1.91)	(-3.13)

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

Low $\mathrm{MAX}^{\mathrm{Fund}}$	2	3	4	5	6	7	8	9	High $\mathrm{MAX}^{\mathrm{Fund}}$	High − Low
0.01	-0.01	-0.00	-0.02	-0.06	-0.07	-0.08	-0.09	-0.09	-0.10	-0.11
(0.47)	(-0.21)	(-0.07)	(-0.44)	(-1.23)	(-1.57)	(-1.56)	(-1.54)	(-1.56)	(-1.53)	(-1.20)

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