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Abstract

The literature has demonstrated that stocks with skewness-like characteristics –*lotteryness*– are the target of a type of investors willing to pay a premium to achieve exposure to skewness. We show that only stocks without options written on them have the potential to attract skewness-seeking investors; furthermore, out-of-the-money options are the dominant security with lottery characteristics for skewness investors. Finally, we find evidence that suggests that skewness-seeking in out-of-the money options ist driven mainly by retail investors, while average negative returns in some at-the-money options seem to be linked to the covered-call strategies of mutual funds.

1 Introduction

Following the COVID-related market crash of last March, a large number of new retail investors flocked to financial markets. Anecdotal evidence suggests that one of the factors fueling this surge was the attempt to fill the void left by the suspension of organized sports and sports betting.[1]

Although only recently has the financial press written broadly about gambling-motivated investing, there is a long –although arguably not mainstream– tradition in the academic literature of studying skewness-seeking –i.e., gambling– in economic decisions.[2] A strand of this literature has focused on the study of individual securities with lottery characteristics and the effect of skewness-seeking on their prices. Brunnermeier, Gollier, and Parker (2007) and Mitton and Vorkink (2007) show that demand for *idiosyncratic skewness* leads to lower expected returns in skewed securities. This is a key theoretical observation that informs the subsequent literature, including this paper.

From an empirical standpoint, a first obstacle in this line of research is to identify what securities investors *ex ante* believe will have a skewed return distribution.[3] Bali, Cakici, and Whitelaw (2011) go around this problem by ranking stocks according to their maximum ten-day return over the previous month –their findings hold for five-day returns as well. This is an easy proxy for skewness-seeking investors. Bali et al. (2011) show that a strategy that buys the top decile and shorts the bottom decile offers a risk-adjusted negative return, suggesting that some investors are willing to pay a premium for these stocks, as predicted in the previously mentioned papers. In the same spirit, Boyer and Vorkink (2014)

[1] "Individuals Roll the Dice on Stocks as Veterans Fret," Wall Street Journal, June 9, 2020.

[2] An influential reference is Friedman and Savage (1948) who introduce a non-standard utility function that can justify the simultaneous but seemingly contradictory demands for insurance and gambling. We provide a more comprehensive analysis of this literature in the next section.

[3] By the nature of the "rare, large events" that usually characterize skweness, we would need long time series to reliably estimate skewness, but it is a stretch to argue that the distributions are stationary enough for time series longer than just a few months to be informative.

introduce the notion of lottery options. Given the truncated nature of options' payoffs, they demonstrate that it is possible to measure skewness directly and, consistent with the previous literature, they show that options with larger right-skewness –larger *lotteryness*– on average yield lower returns. Complementing these works, Byun and Kim (2016) study the behavior of options whose underlying is a lottery-like stock –in particular, at-the-money or close to at-the-money options; they show that they are overpriced, and a short-long strategy based on the lotteryness of the underlying pays an abnormal risk-adjusted expected return.

In this paper we study, for the first time in the literature, the interaction between lottery stocks and lottery options. In particular, what drives the *choice between lottery stocks and lottery options* among gambling-motivated investors, as well as the effect of the introduction of options on the lottery properties of the stocks, including their price. Hence, we also contribute to a strand of the financial literature that studies whether options have an effect on the price of the underlying securities.[4] We analyze a channel previously unexplored in this literature, the effect of options on stocks with lottery properties through the demand for skewness. In addition, we also investigate what types of investors are involved in the trading of lottery options.

We first track lottery stocks from 1963 to date. We follow Bali et al. (2011) and use average 5-day and 10-day returns over the last month to classify stocks in terms of "lotteryness", from the highest maximum to the lowest maximum returns over these time periods. We denote the variable that measures lotteryness of stocks according to this methodology *MAX(10)*. For options, the data with all the details we need is available from 1996. To determine what options are in the lottery category we use the methodology of Boyer and Vorkink (2014). We denote the variable that measures lotteryness of options

[4] See, for example, Ni, Pearson, Poteshman, and White (2018) and its references for a review of this literature. That particular paper differentiates the effect on the stock price through the hedging position of the option traders depending on their gamma, i.e., whether they hedge a long or a short position.

according to this methodology *BV-SKEW*. As in previous work, the lottery options we study are call options. We use put options for some of our robustness tests.

Our first result provides a preview of the rest of the findings of the paper. We sort out stocks in deciles in terms of their lotteryness, that is, from highest to lowest maximum average 10-day returns over the previous month, MAX(10) –we repeat it with 5-day returns. Initially, we consider stocks from 1963 to 1996, the first date for which we have options data available from Optionmetrics. This is also arguably a point at which option markets have evolved to be easily accessible to retail investors. We verify the finding of Bali et al. (2011) and show that portfolios long in stocks in the top decile in terms of 10-day return over the last month, and short in the bottom decile have a negative, statistically significant, risk-adjusted return –same result when we repeat the exercise with 5-day returns. This is consistent with investors with gambling preferences overpaying for the lottery stocks. However, the result disappears after 1996 and, although the sign of the return of the long-short portfolio is still negative, it is not significant anymore.

We break down the sample of stocks after 1996 into those with options written on them and those without. We find that the difference between the sample up to 1996 and after 1996 is due to stocks with options: The sign of long-short portfolio returns for stocks without options written on them is still negative and statistically significant. However, that is not the case for stocks with options written on them. Our conjecture –later verified in other tests– is that investors with gambling preferences choose options over stocks, when options are available, to make the most of the embedded leverage offered by these assets. This mechanism contributes to the decay of the MAX strategy for optionable stocks. Using more limited data, we study options introduced before 1996. Consistent with our previous results, we find that the MAX strategy offers a negative but insignificant return for stocks with options starting from June 1977.[5]

[5]Our monthly series starts June 1977, as we have enough stocks in each of our decile portfolios from that date.

Next we perform a preliminary analysis of lottery options. Inspired by the work of Byun and Kim (2016) we sort out options into at-the-money (ATM) and out-of-the-money (OTM). We confirm the result of Byun and Kim (2016) that a long-short strategy with ATM options sorted according to the lotteryness of the underlying yields a significant negative expected return. However, that is not the case for OTM options as the difference in option returns is now positive but insignificant. Furthermore, we allocate options into deciles based on their option lotteryness –using the methodology of Boyer and Vorkink (2014), BV-SKEW– from low to high ex-ante skewness. We find that a long-short strategy with ATM options yields a positive but not significant expected return, while with OTM option it delivers returns three times bigger. In other words, investors are willing to give up returns of more than 46% per month for the lottery potential of OTM options. Following Bali et al. (2011), we perform cross-sectional Fama and MacBeth (1973) two-pass regressions controlling for factors such as liquidity, size or momentum, and verify that our previous findings hold.

In the tests we have discussed so far we consider lottery features stocks and options separately. In the next set of tests we double-sort lottery stocks and lottery options to analyze their interaction. We start with ATM options and their underlying stocks. While lottery stocks are not statistically significant after 1996 when considering the whole universe of stocks –or stocks with options–, we find that returns of lottery stocks are negative when ATM lottery options (e.g., with a high BV-SKEW measure) are attached to them. In addition, we find that returns of long-short strategies of these ATM options based on the lottery characteristics of the underlying are also negative and highly significant –as shown in Byun and Kim (2016).

On the other hand, we find that only the option returns of spread portfolios of OTM options sorted on BV-SKEW on average are negative and statistically significant. This is unrelated to the lotteryness of the underlying –unlike in the case of ATM options– as the expected returns are negative and significant for any level of MAX(10). We also show that in both BV-SKEW and MAX-sorted portfolios stocks do not exhibit the statistically significant negative returns that would indicate lottery demand.

As with the single-sort tests, we complement the double-sort test with a cross-sectional regression that sorts into three bins options and stocks according to the lotteryness parameters –MAX(10) and BV-SKEW– and includes in the regression the other parameter value and the controls used before. This test verifies the previous results. However, it is important in our analysis because it lays the foundations of the following and final direct test of the relationship between lottery stocks and lottery options.

In sum, the effect of lottery characteristics on returns is very different for ATM options and OTM options, and their respective underlying stocks. We conjecture that it might be the result of different clienteles for each group of securities. To explore this avenue we analyze order imbalances. Although the available details on the parties responsible for the type of imbalance –sell-driven or buy-driven– are limited, we clearly establish that a group of investors that includes mutual funds and retail investors is responsible for net sales of ATM call options with high MAX and high BV-SKEW. This is consistent with the pervasiveness of covered called strategies carried out by mutual funds. On the other hand, the same set of investors are net buyers of OTM call options, regardless of the level of MAX. This is consistent with skewness-seeking retail investors as drivers of the large negative average returns we observe in OTM options with lottery characteristic because these investors are willing to pay a premium for right-skewed returns.

We explore further our conjecture about the linkage between the negative average returns of ATM options in high MAX-high BV-SKEW bins and the covered call strategies frequently used by mutual funds. From their filings, we first sort mutual funds into those that take positions in options (long or short) and those that do not trade options. Next, we study the average stock holdings of the mutual funds in each of the MAX/BV-SKEW bins across mutual funds that trade in options and we compare them with the holdings of mutual funds that do not trade in options. We find that the relative holdings of stocks in the high MAX-high BV-SKEW bins are relatively much larger for mutual funds that trade in options than for those that do not. The options written on these stocks are the ones that show negative returns. Therefore, this reinforces the possibility that these average negative returns obtain because mutual funds with relatively large exposure to the stocks write their ATM options –easier to write that the less liquid OTM options.

Additionally, we perform several robustness tests and verify that our main results hold. In particular, we consider earlier –to our default starting point 1996– option introductions to rule out that the disappearance of lottery properties of stocks with options written on them is not due to some other factor associated with our starting date. In other tests we consider different moneyness intervals, as well as different choices for our tests of options withing intervals. Finally, we add as control variables measures of options liquidity.

The rest of the paper is organized as follows: section 2 provides a literature review; section 3 describes the data and portfolio construction methodology; in section 4 we present our main empirical results; section 5 consists of the robustness tests; section 6 is a short sections of conclusions.

2 Skewness-Seeking Literature

Friedman and Savage (1948) point out that standard utility functions cannot explain why households would buy insurance and, simultaneously devote some resources to gambling. They suggest a different type of utility function that is not strictly concave and can explain this seeming contradiction. Their suggested utility function, though, is *ad hoc* in that it is not based on any axiomatics. Subsequent literature has attempted to explain what type of preferences or microeconomic foundations would yield such an utility function. An influential idea is Ng (1965) who shows that good indivisibility would explain the convex segments of the utility function. In a simultaneous but independent analysis, the prospect theory of Kahneman and Tversky (1979) and Tversky and Kahneman (1992) proposes a *value function* that is reminiscent of the Friedman-Savage utility.

Intuitively, these convex utility functions (or parts of an otherwise concave utility function) denote risk loving attitudes that might justify embracing additional volatility or positive skewness –even if associated with negative expected returns. Another recent justification, also suggested in the psychology literature (e.g., Lopes and Oden, 1999) that leads to possible convexities in the utility function is *aspirational utility*, as in Diecidue and Van De Ven (2008). Similarly, status-seeking, related to the notion of conspicuous consumption leads to convex kinks in the utility function (e.g., Lee and Zapatero, 2020). Many variations of these type of preferences (for example, relative wealth concerns) can explain convex utility functions for which skewness-seeking might be optimal.

There is another strand of the literature that takes skewness-seeking as given and studies its implications for securities. Markowitz (1952) and Kraus and Litzenberger (1976) study equilibrium implications of the demand for *systematic skewness*. Harvey and Siddique (2002) show that systematic skewness helps to explain the cross-section of stock returns. Also, Brunnermeier et al. (2007) and Mitton and Vorkink (2007) show that demand for *idiosyncratic skewness* leads to lower expected returns in skewed securities. Barberis and Huang (2008) reach a similar conclusion from an equilibrium model derived from the postulates of prospect theory.

Finally, we mention the empirical literature that studies the demand of stocks and options as lotteries. Kumar (2009) documents that households prone to buy lottery tickets are also more likely to invest in stocks with lottery characteristics. Doran, Jiang, and Peterson (2012) find that New Year's gambling affect the performance of stocks with lottery payoffs. Specifically, out-of-the-money stock options are more expensive and heavily traded in January than in other months of the year. Blau, Boone, and Whitby (2014) investigate the role of gambling in the volume and volatility of the stock and option markets. The authors find that the call option ratios are much higher for stocks with lottery-payoffs demonstrating that call options of lottery stocks are highly traded and thus affect the price of the underlying asset. Dorn, Dorn, and Sengmueller (2014) find a negative relation between jackpot and trading of stocks with lottery-like payoffs.

3 Data and Portfolios Construction

3.1 Stock and Option Data

Stock Data. We collect daily and monthly stock returns as well as monthly trading volume from the Center for Research in Security Prices (CRSP), considering only New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ as well as common stock with share codes 10 and 11, financials and non-financials. Our data span the period from July 1963 to December 2018. We also use accounting information for these stocks from the Compustat database.

Option Data. We obtain options data from the OptionMetrics IvyDB database and for all exchange-listed options on U.S equities. We specifically use end-of-day bid and ask quotes, trading volume, open interest, strike prices, deltas and implied volatility. This data is available from January 1996 until December 2018. In our analysis, we mainly focus on at-the-money (ATM) and out-of-the money (OTM) call options as they exhibit lottery features (e.g., Byun and Kim, 2016; Boyer and Vorkink, 2014). We define moneyness as the ratio between the price of the strike price of the option (i.e. X) divided by the underlying asset (i.e. S). Then, we select only one option per underlying asset that satisfies our criteria. Specifically, we define as ATM options those options with moneyness between 0.95 and 1.05 (i.e. $0.95 < X/S < 1.05$) that is close to 1 and OTM options exhibit the highest moneyness ratio above 1.05 (i.e. X/S>1.05).

Filters. We apply a number of filters in the data in order to ensure tradability and avoid outliers (e.g., Byun and Kim, 2016; Boyer and Vorkink, 2014). We eliminate observations of the option data with particular characteristics. Specifically, we keep options with an "index flag" of zero and only the option for which the underlying asset is a common stock. We do not consider the options with expiration date at the market open of the last trading day. We also control for option with number of shares different than 100 (i.e. a "special settlement flag" that it is different from zero). In addition, we do not include options with missing bid prices (i.e. values of 998 or 999) or bid-ask spreads that are below zero on the rebalancing date (i.e. the last date of the month). Furthermore, we delete duplicates (i.e. options with the same underlying asset, maturity date, and strike price at the rebalancing date) observations with zero open interest and options with less than zero or missing implied volatility and volume (these filters are described in detail in Appendix B).

Option Order Imbalances. We obtain data on Option Order Imbalances using signed option trading volume from the International Security Exchange (ISE) Open/Close Trade Profile database. This data has daily buy and sell volume trades and prices for each option traded at the ISE but is only available for a part of our sample period from 2006-2016. For this shorter sub-period, we extract data on the direction of each trade and on whether the trades open new positions or close existing positions. Trades reported in the ISE Open/Close database represents more than 30% of the total trading volume in individual equity options during our sample spanning January 2006 to December 2016. Following Pan and Poteshman (2006); Ge, Lin, and Pearson (2016) we focus on opening trades as they are generally more informative than closing trades. In particular, we compute signed call trading volume to stock trading volume (C/S) for a period starting from the first trading day immediately following the expiration Saturday of the month until the last day of the month. We also use the same time period to compute option order imbalances following Bollen and Whaley (2004) and defined as:

$$OIMB_{i,t} = \frac{\sum_{i=1}^{N}(Buy_{i,t} - Sell_{i,t})}{\sum_{i=1}^{N} Buy_{i,t} + Sell_{i,t}} \tag{1}$$

where $\text{Buy}_{i,t}$ ($\text{Sell}_{i,t}$) represents buyer (seller)-initiated transactions and is defined as Open $\text{Buy}_{i,t}$ (Open $\text{Sell}_{i,t}$) for option i at time t. In other words, a positive (negative) option order imbalance means that investors tend on average to buy (sell) call options assigning upward (downward) price pressure on call options.

Institutional Ownership. We obtain end-of-quarter institutional stock holdings as they are reported in the 13F form of the Security and Exchange Commission (SEC). These data are collected from Thomson Financial *via* the Wharton Database and span the period of April 1981 to December 2018.

Short Interest. Our measure of short interest follows Rapach, Ringgenberg, and Zhou (2016). Specifically, we obtain mid-month and end-of-month short interest data from Compustat which reports the total number of shares that are held short in a given firm for NYSE and AMEX stocks beginning in January 1973 (in our sample we start from January 1996) and for NASDAQ stock since 2004. As month-end data is only reported after September 2007 we use only mid-month numbers so as to be consistent with the length of our data sample. To this end, we compute the proportion of shares held short by dividing the mid-month short interest data by each firm's mid-month shares outstanding obtained from the daily CRSP database.

Option Returns. We define the return of holding a call option to maturity as follows:

$$RX^{c}_{j,t:T} = \frac{\max(0, S_{j,T} - X_j)}{0.5(P^{ask}_{c} + P^{bid}_{c})} - 1, \tag{2}$$

where X_j is the strike price and $S_{j,T}$ is the price of the of the underlying asset j at maturity or the rebalancing date (i.e. time T). P^{ask}_{c} (P^{bid}_{c}) is the ask (bid) price of the call option at time

t. We mainly focus on call options due to the fact that gamblers have higher preferences for this kind of options (e.g., Shefrin and Statman, 2000).

3.2 Lottery Stocks and Options Portfolios

In this section we analyze the construction of the stock and option portfolios with lottery characteristics. Both portfolios follow a one-month formation and rebalancing periods.

MAX Portfolios. Following Bali et al. (2011), we use daily stock returns to calculate the maximum daily stock returns for each firm every month. Specifically, at the end of each month $t-1$, we sort stocks into deciles based on their maximum average 5-day (MAX (5)) or 10-day (MAX(10)) daily return that month and compute the value-weighted average return of each of the portfolios during month t. Then our MAX spread (i.e. HML) portfolio contains a long position in the highest MAX portfolio while short-selling the lowest MAX portfolio.[6]

Lottery Option Portfolios. Similarly to the case of MAX portfolios, we form portfolios of call options on the last trading day of each month $t-1$ and consider options that expire the following month.[7] At the end of each month $t-1$, call options (i.e. RX^c) are allocated into deciles based on their ex-ante skewness (BV-SKEW) (Boyer and Vorkink, 2014) and compute the equally-weighted average return of each portfolio during month t. Then our option lottery spread (i.e. HML) portfolio buys the options in the highest BV-SKEW portfolio while short-selling the options in the lowest BV-SKEW portfolio.

[6]Here we consider stocks with and without options only. We define stocks with options those stocks that have options in our sample after eliminating those that do not satisfy the filters discussed in the data section.

[7]The main reasons for using monthly options is to alleviate concerns about overlapping data and lower trading volume. However, our results are improved once we consider longer expirations.

4 Empirical Results

We present in this section our main results. First, we investigate separately the two *pure* strategies –investing in lottery stocks and investing in lottery options– and analyze their respective performances. Next, we evaluate the performance of *blended* strategies by allocating options and stocks into portfolios sorted on their own lottery characteristics –MAX for lottery stocks and BV-SKEW for lottery options– and the lottery characteristics of each other. In other words, we investigate investors' choices when both stocks and options are lotteries.

4.1 Univariate Sorts

Lottery Stocks. First, we examine the time-series behavior of stocks with lottery characteristics, as explained in the previous section. Table 1 reports average returns of stocks sorted into 10 portfolios based on their previous month average 10-day (MAX(10)) maximum daily return.[8] *Panel A* of Table 1 reports results from July 1963 to January 1996 while *Panel B* displays MAX returns from January 1996 to December 2018.[9] January 1996 is not only the first date options data from Optionmetrics are available to construct our measure of option lotteryness but also a point in time at which options arguably are broadly available to retail investors.[10] Our objective is to understand what happened to trading in lottery stocks when options became available as a possible substitute. In particular, if investors were still willing to pay a premium for lottery stocks.[11] Indeed we find that while

[8]Results are similar for portfolios sorted on the previous month average 5-day (MAX(5)) maximum daily return and they are available on demand.

[9]We start our analysis from 1963 so as to have results comparable with similar studies in the literature (e.g., Bali et al., 2011). In addition, results for the full sample (January 1963-December 2018) are similar to *Panel A* and they are available upon request.

[10]In the robustness section we also consider equity options from 1973 to 1996 and show that our results do not depend on the choice of our sample

[11]There is a literature that studies the effect of option trading on the price of the underlying. For example, Sorescu (2000) and Wang (2015).

the excess returns of lottery stocks are negative and highly significant until 1996 (*Panel A*), demonstrating that investors were willing to pay a premium for them, such is not the case after 1996 –the sign of the average payoff is still negative, but not significant.

More precisely, we report excess returns of decile portfolios of stocks sorted based on previous month MAX returns. T-stats represent Newey and West (1987) *t*-statistics corrected for heteroskedasticity and autocorrelation (HAC) using the optimal number of lags as in Andrews (1991). HML represents a spread portfolio that buys stocks with past high daily maximum returns while selling stocks with low daily maximum returns. We find that from 1963 to 1996 this strategy renders a highly negative and statistically significant return even after adjusting for the five Fama and French (2014) factors, consistent with lottery stocks being overpriced because investors are willing to pay a premium for them. All portfolios are value-weighted.[12]

Yet, this changes when we examine the period from 1996 until the end of the sample. In particular, we observe in *Panel A* that the return of the spread portfolio becomes insignificant. This suggests that investors are not willing to pay a premium for lottery stocks, possibly because trading in the corresponding options is cheaper or provides more "bang for the buck" given the implicit leverage in options. There might be at play other factors (e.g., illiquidity) that we test in another section of the paper.

Panel B reports average returns of MAX portfolios after controlling for the existence of options written on the stock. We define stocks with options as stocks that have at least one active call option written on them during the rebalancing period (e.g., the last trading day of each of month, when we form our MAX portfolios). We find that the MAX strategy is not significant for stocks *with* options. Yet, the MAX strategy is significant for stocks without options for both MAX(5) and MAX(10) portfolios.

[Table 1 about here.]

[12] However, as we have verified, these results hold regardless of the weighting scheme.

Lottery Stocks Demand. The previous analysis demonstrates that the lottery premium of stocks becomes smaller after 1996. This is arguably due to the availability of options, as the premium remains for lottery stocks without options. To gain further insight we examine whether the trading volume of the lottery stocks –which serves as a proxy for aggregate demand– is associated with the overvaluation. In particular, we conjecture that the negative and statistically significant premium for lottery stocks without options will be associated with higher demand. On the other hand, the demand of lottery stocks with options should be independent of their lotteryness, as skewness-seeking investors prefer to invest in the corresponding options. Table 2 shows that the trading volume *increases* for stocks without options with the measure MAX(10), and this increase is (very) significant. Yes, for stocks with options, there is no observable pattern. Understandably, the trading volume of stocks without options is on average much smaller as these are smaller companies, which explains why there are no options on them.

[Table 2 about here.]

Lottery Options. In the same vein as our initial study of lottery stocks, we allocate options into decile portfolios based on their ex-ante skewness (BV-SKEW). This is the measure introduced by Boyer and Vorkink (2014) who show that, similarly to the case of stocks, there is a negative relation between options' lotteryness and returns, that is, investors are willing to pay a premium to hold these options. Since many stocks have multiple options, to simplify our analysis –and in line with similar studies– we select options that expire the following month from two different moneyness intervals, one from each. Accordingly, we denote as *at-the-money* (ATM) options those that have moneyness levels around 1 (i.e., $X/S \sim 1$); in particular, we choose from the interval between 0.95 and 1.05. Likewise, the options we label *out-of-the-money* (OTM) have moneyness above 1.05. In the robustness section we consider different moneyness intervals for ATM and OTM options and take into account more than one option per stock, and get similar results.

Table 3 presents mean returns of decile portfolios of options sorted on previous month MAX of the underlying stock and ex-ante skewness (BV-SKEW). We include alphas of the Fama and French (2014) five-factor model for the spread portfolios. Our t-statistics control for autocorrelation and heteroskedasticity following Newey and West (1987) with the optimal number of lags as in Andrews (1991). Option returns are equally-weighted. *Panel A* reports MAX-sorted option returns and *Panel B* shows BV-SKEW-sorted option returns.

Panel A shows that ATM options sorted based on the maximum daily return of the underlying security are *overvalued* for high values of MAX –lotteryness of the underlying– and the spread portfolio renders a negative and statistically significant return (Byun and Kim, 2016). On the other hand, when OTM options are sorted according to MAX(10) the spread portfolio does not display a negative significant return.

Finally, we note (*Panel B*) that, unconditionally –i.e., regardless of their underlying–, ATM options are not overpriced –i.e. they do not exhibit lottery-like payoffs, even if their lottery characteristics BV-SKEW are high. This is in contrast with OTM options, as the average spread portfolio sorted by BV-SKEW produces negative and statistically significant returns. More precisely, lottery seekers seem to prefer OTM options to ATM options, maybe because they are cheaper and their implicit leverage magnifies the lottery attributes of the underlying asset (e.g., Ni, 2008; Boyer and Vorkink, 2014). In sum, we find, that investors are willing to pay a premium only for the lottery characteristics of OTM options.[13]

[Table 3 about here.]

[13]We also offer cross-sectional regression in Table A2 of the Internet Appendix that control for other determinants of stock returns and the results are robust.

Discussion. Overall, we find a different selection of lottery securities depending on whether the options written on the stock are ATM or OTM. In particular, for ATM options we find that a long-short strategy sorted according to MAX(10) yields a significant negative expected return. In contrast, when sorted according to BV-SKEW the same strategy yields a positive but not significant expected return. However, in the case of OTM options, we observe that when they exhibit lottery characteristics –i.e., high BV-SKEW– lottery investors prefer them and ignore their underlying stock, apparently even if it has lottery characteristics –high MAX. In fact, investors are willing to give up returns of more than 48% per month for the lottery potential of OTM options. We conclude that there is *substitution* between OTM options with lottery characteristics for the corresponding stocks. In the next sub-section we further analyze these relationships.

4.2 Bivariate Sorts

To further investigate the effects of skewness-seeking strategies, we perform a double-sort analysis of stocks and options according to their lotteryness characteristics. In particular, we study if the mispricing of ATM and OTM options documented in Table 3 depends on whether both the option and the underlying stock exhibit lottery characteristics jointly. To this end, we double-sort stocks into portfolios based on their own MAX measure and the BV-SKEW measure of the relevant options (ATM and OTM) written on them. Similarly, we double-sort options, both ATM and OTM, into portfolios based on their own BV-SKEW measure and the MAX measure of the underlying stock. Specifically, we match a stock with the ATM option with moneyness between 0.95 and 1.05 that is closer to 1 and the OTM option with the highest moneyness ratio above 1.05. This allows us to consider only one option per stock for each moneyness category –and robustness tests show that our results do not depend on the particular selection rule.

Before we study pricing implications, we examine the range of lottery characteristics and the interaction of our two measures, MAX and BV-SKEW. We want to make sure that the two measures provide an adequate range and, more importantly, if they are somehow connected. With that purpose, we take the full sample of stocks with their two associated options, one ATM the other OTM, and compute their monthly MAX –for the stocks– and BV-SKEW –for the options. We double-sort them in three quantiles for each measure and report the average MAX (*Panel A*) and BV-SKEW (*Panel B*) characteristics in Table **??**.

Next, we study the results from our double-sorting of the returns of lottery stocks and lottery options according to the lotteryness measures, MAX and BV-SKEW. This is presented in table 4. One problem with this approach is that it does not take into consideration other possible factors that can affect the prices of the securities. For that reason, and in line with the related literature, we follow our double-sort analysis with cross-sectional regressions where we control for several factors considered in the literature. In table 4 we report independently our findings for both ATM and OTM options: as we will see the results are qualitatively different for each class of options.

ATM Options/Underlying Stocks. *Panel A* of table 4 shows average option returns sorted on BV-SKEW and MAX. In line with table 3, we find that ATM options sorted by the standard options measure of lotteryness, BV-SKEW, do not exhibit lottery-like payoffs, despite a substantial spread between the low- and high-BV-SKEW terciles. In contrast, we corroborate the result of Byun and Kim (2016) that the returns of spread portfolios of ATM options sorted on the MAX measure, the lotteryness of the underlying, are always negative and significant. *Panel B* shows the corresponding average stock returns of BV-SKEW and MAX-sorted portfolios. The MAX strategy is only marginally significant for stocks with whose ATM options display a high BV-SKEW, yet the spread in returns is substantially larger for the corresponding ATM options. This could be because the skewness-seeking investors prefer to trade the options. Another possible factor might be the price impact in the stocks produced by the option market maker through their position in stocks for hedging purposes – Hu (2014). In the next section, we will study this in detail.

OTM Options/Underlying Stocks. The main result for OTM options in table 4 is that, unlike for ATM options, the BV-SKEW spread portfolios are always negative and significant, both statistically and from an economic standpoint, regardless of MAX. Like for ATM options, we find that option returns of MAX spread portfolios are significant for higher levels of BV-SKEW –we will see that this changes when we introduce controls. Regarding spread portfolios of the underlying stocks, similarly to the case of ATM options, we find that they only offer negative returns marginally significant in the case of high MAX and high BV-SKEW –the latter at a fraction of the size of the spread for the options. In addition, controls affect these results.

In sum, this first approximation in our analysis suggests that skewness-seeking investors favor OTM options. In the cross-sectional regressions we introduce controls to study the robustness of the results of table 4.

[Table 4 about here.]

Cross-sectional Regressions. In the spirit of Bali et al. (2011), we run Fama and MacBeth (1973) cross-sectional regressions of option and stock returns on the previous period MAX and BV-SKEW as well as on a number of lagged control variables (e.g., log size (Ln(Size)), log stock price (Ln(Price)), institutional ownership (IOR), book-to-market (B/M), debt-to-assets (D/A), turnover, idiosyncratic volatility (IVOL), stock illiquidity (ILLIQ^{Stock}), reversals (REV) and momentum (MOM)) that capture different dimensions of the lottery strategies. Table 5 reports the results of the following cross-sectional regression:

$$\text{RX}_{i,t+1} = \gamma_{0,t} + \gamma_{1,i}\text{MAX}(10)_{i,t} + \gamma_{2,i}\text{BV-SKEW}_{i,t} + \gamma'_{3,i}\mathbf{Z}_{i,t} + \varepsilon_{i,t+1} \tag{3}$$

where $\text{RX}_{i,t+1}$ represents option (*Panel A*) or stock (*Panel B*) returns of asset i, and $\mathbf{Z}_t$ is the set of control variables. Table 5 reports average coefficients and average adjusted R^2s of the previous regression, as well as HAC t-statistics.

Regarding ATM options and their underlying stocks, and consistent with the previous simple double-sort analysis, we obtain negative and significant coefficients of MAX for both the options and the underlying stocks, especially when BV-SKEW is high. The BV-SKEW coefficients, when we introduce controls, are either insignificant or positive, contrary at odds with a lottery effect.

With respect to OTM options, the BV-SKEW coefficients are always significant. The MAX coefficient for stocks is significant only for the high BV-SKEW tercile.

[Table 5 about here.]

Overall, we find that in the case of ATM options, their lottery-overpricing and that of stocks go hand in hand, driven by the lottery characteristics of the stocks. On the other hand, in the case of OTM options, their overpricing depends exclusively on their lottery characteristics, suggesting a *substitution* effect, as the lottery effect on stocks is very small. In addition, their overpricing is substantially higher than that of ATM options. Next we try to identify who the “skewness-seekers” are.

4.3 Lottery Demand: Options Order Imbalances

In the previous sections we have established that the relation between lottery stocks and their associated lottery options are different, depending on whether the options are ATM or OTM. To further analyze these different patterns, we investigate if they are the result of different types of traders. Unfortunately, it is not possible to perfectly identify originators of option trades. However, as described in section 3, the ISE –where a sizable proportion of option trades take place– offers some partial information. First, for each option it provides the net daily trade volume, defined as the difference between the total volumes of buyer-originated and seller/writer-originated trades. In addition, and very importantly, ISE sorts traders into *customers* and *firms* and discloses daily net volume corresponding to each type of trader.[14] Although the definitions are relatively broad, we can roughly consider customers as the traders looking for risk-exposure in options, including retail traders, and firms the professional traders that try to benefit from the overpricing or underpricing of options –see, for example, Eisdorfer, Goyal and Zhdanov (2020). The normalized order imbalances are presented in Table 6.

The left side of all three panels of Table 6 shows time-series averages of normalized mean order imbalances of ATM call options. The right side presents the order imbalances for OTM options. Panel A is for the aggregate, Panel B for customers and C for firms, as characterized above.

The first observation is that the larger imbalances are the result of customers orders. The imbalances for firms are substantially smaller, especially for ATM options. Therefore, we focus on Panel B, customers, where most of the activity seems to take place. The main fact in this category is that the signs of the imbalances are different from ATM and OTM

[14]According to the ISE, customers refers to retail investors, as well as investment banks such as Morgan Stanley and Goldman Sachs who execute trades on behalf of large customers or hedge funds. Moreover, firms are investment banks who place orders from their own accounts or on behalf of an another broker dealer who is not a member of the exchange.

options: customers write ATM call options and buy OTM call options. Regarding the ATM options, the volume is larger for high MAX and BV-SKEW measures. A comparison between this pattern and that of Table 4 for ATM options suggests that although customers write calls regardless of the MAX/BV-SKEW measures, they write more intensively those that are overpriced. A possible explanation of the previous facts is that the segment of customers responsible for the negative imbalances consists mainly of mutual funds: Mutual funds often implement covered calls strategies, that is, write calls of stocks in their portfolios. They might prefer to write predominantly those that are overpriced. Regarding OTM options, customers buy these calls, and they do so especially for the hight BV-SKEW, the lottery options, expressing a skewness-seeking motivation. Firms trade options at a much lower rate, and always buy calls, ATM and OTM. In the case of OTM options, we do not observe the skewness-seeking preference we observe among customers.

Therefore, although we do not have granular data on the traders responsible for the order imbalances, the evidence is consistent with skewness-seeking investors for OTM options, but not for ATM options. This supports our conjecture based on the previous tables that the overpricing of some ATM options is linked to the price of their underlying, not the result of a lottery strategy, as the category of investors that includes the natural candidates to follow lottery strategies –customers– is not buying these calls, but actually selling them. We further conjecture that this option writers are likely to be in good part mutual funds implementing covered calls strategies, rather than retail investors. To further investigate this possibility, in the next subsection we analyze stock holdings of mutual funds that declare involvement in option trading.

[Table 6 about here.]

4.4 Stock Ownership of Mutual Funds with Positions in Options

In the previous section we conjectured that the negative order imbalances we observe for ATM options in the category of customers could be the result of covered call strategies, frequently used by some mutual funds. To further investigate this, we collect information about mutual funds holdings of stocks. Of course, mutual funds use many different strategies and their holdings of stocks need not be directly related to their use of options, for which we have very limited information. However, despite all these limitations, we want to see if there is some relation between stock holdings and option trading imbalances, as indirect evidence of our conjecture. To this end, we first identify mutual funds that disclose positions in options. Next, in each of the nine bins resulting from our double-sorting classification based on MAX/BV-SKEW measures, for all mutual funds with positions in options, we compute the time-average total holdings across all the mutual funds of underlying stocks. That is, we identify the options in each of the bins and divided the total number of shares of the underlying stocks owned by these funds by the number of shares outstanding of that particular stock, as a way to normalize the level of holdings[15].

We show the results in Table 7, sorted based on the previous period MAX and BV-SKEW, so that we can compare with the pattern of options imbalances.[16] *Panel A* reports summary statistics of mutual funds with option holdings: Total number of funds with positions in options, the percentage of these funds that write options the percentage that buy options and the percentage that buy and sell options. A large majority of mutual funds write options. *Panel B* presents the time-series average of the ratio of total stock ownership –of mutual funds with positions in options– over shares outstanding, computed as explained

[15]To construct our dataset, we merge the N-SAR filings with the CRSP mutual fund and Thomson S12 holdings databases. We use algorithmic string matching methods as well as manual matching in order to match N-SAR, CRSP and Thomson S12 funds by their names. The N-SAR filings offer semiannually information regarding the use of options. Based on this filings, Natter, Rohleder, Schulte, and Wilkens (2016), for example, draw conclusions about option strategies by mutual funds.

[16]We select mutual funds whose N-SAR filings report trading of single stock options (Item 70B), balance sheet data that includes written equity options (74R3), and a positive market value of purchased equity options (74G).

before. *Panel C*, for comparison purposes, shows the time-series average of the similarly computed stock ownership ratio for the remaining mutual funds that do not report positions in options[17] What we are interested on is the pattern across all nine bins and how the patterns in Panel B compares to the patterns in Panel B of Table 6, as mutual funds belong to the Customer category, and the patterns of Panel C.

We first discuss the case of ATM options and corresponding stock holdings. First, it is clear that the allocation of stock holdings across different lottery measure bins is very different for mutual funds with and without positions in options: funds with positions in options favor stocks with high MAX or/and BV-SKEW, while funds without favor low measures. Of course, there are many factors at play that can be responsible for this discrepancy. However, when we compare with Panel B of Table 6 we observe that option imbalances and stock holdings of mutual funds with positions in options display very similar patterns, as the largest negative imbalances happen for high MAX and BV-SKEW, precisely the stocks on which these mutual funds have the largest relative holdings. Arguably these stocks are more volatile –and that is the reason why they score high in MAX and/or their options score high in BV-SKEW; it is possible that funds which take positions in options are willing to hold larger proportions of them because they drive revenue from writing their options. The low returns on these options might be an outcome of this selling pressure.

Regarding stocks holdings corresponding to OTM options, mutual funds with positions in options in general also favor those with high MAX/BV-SKEW, although the patter for the latter metric is not as strong as in the case of ATM options. The comparison with Table 6 is not as straightforward, though; it is possible that mutual funds are also writing these options, but the prevalent effect is the skewness-seeking through long positions in calls that we documented in previous results. , but there is no patter regarding BV-SKEW.

[17]The numbers in Panel C are much larger than in Panel B because only a small fraction of funds have positions in options, therefore their total holdings over all of them are substantially smaller.

In sum, limitations in the data details do not allow us to draw definitive conclusions about the relationship between stock holdings by mutual funds and their option trading strategies. However, we observe that mutual funds that take positions in options favor the stocks for which the negative imbalances previously documented for ATM options are the largest. This is consistent with the possibility that the lower returns in ATM options are due to the covered-call strategies used by many mutual funds, and not exclusively to the lottery properties of the stocks and options. In the case of OTM options the trade imbalances are positive, consistent with the existence of skweness-seeking investors different from mutual funds, possibly retail investors.

[Table 7 about here.]

5 Robustness Tests

5.1 Earlier Option Listing

The standard database of option prices, that we use in this paper (Optionmetrics), starts in 1996. However, the CBOE provides information about listing and delisting of options from 1973. Using this information, we construct another database (without option prices) with the set of all stocks with options trading from 1973.[18] We use it in the following robustness tests.[19]

First, we replicate *Panel B* of Table 1. The new results are presented in Table 8. Our monthly series starts June 1977 as we have enough stocks in each of our quantile portfolios from that date. *Panel A* reports raw returns and alphas –using Fama and French (2014)– of

[18]If an option is delisted, we consider the corresponding stock as non optionable after the period of delisting and until a new option is introduced. Our results are not affected by this filter.

[19]We could have included this data in Table 1, but for time consistency purposes, all our previous tests start in 1996, the first year included in Optionmetrics.

stocks without options allocated into deciles based on MAX(5) and MAX(10) from June 1977 to December 2018. We find, in line with *Panel B* of Table 1, that the MAX strategy renders negative and statistically significant returns. *Panel B* of Table 8 extends the universe of optionable stocks based on their option introduction date before 1996. We find that the MAX strategy offers areturn that is not statistically different than zero. This finding shows that the starting point of our data does not affect our result that stock with options do not show lottery properties, but stocks without them do.

[Table 8 about here.]

5.2 Option Trading Frictions

Our set of control variables encompasses several aspects of stock trading. In addition, frictions in option trading could be behind the results observed in the previous section. To analyze this possibility, we run cross-sectional regressions of both stock and option returns on MAX or BV-SKEW, a number of stock-level control variables, a measure of options liquidity (or, more precisely, lack of liquidity, the bid-ask spread), and a proxy of limits to arbitrage.[20] Overall, the model takes the following form:

$$\mathrm{RX}_{i,t+1} = \gamma_{0,t} + \gamma_{1,i}\ \mathrm{Lottery}_{i,t} + \gamma_{2,i}\mathrm{ILLIQ}_{i,t}^{Options} + \gamma_{3,i}\mathrm{Option\ Demand}_{i,t} + \gamma'_{4,i}\mathbf{Z}_{i,t} + \varepsilon_{i,t+1} \quad (4)$$

where $\mathrm{RX}_{i,t+1}$ denotes the stock or option return of asset i; "lottery" denotes the particular lottery characteristic considered in the cross-sectional regression (either MAX or BV-SKEW); $\mathbf{Z}$ is the set of control variables. Table 9 reports average coefficients and average adjusted R^2s of the empirical model of (4) for portfolios with different levels of MAX and BV-SKEW.

[20] Specifically, we construct an option demand measure that is defined as the ratio of the selected call option's open interest at the end of the month over the monthly trading volume of the underlying stock.

With respect to ATM options, in (*Panel A*) we find that illiquidity and option demand cannot explain the cross-section of ATM call option returns with high BV-SKEW (lower panel). In *Panel B* we observe the same pattern for the underlying securities. On the other hand, we find that MAX remains a strong negative predictor of options and stocks even after controlling for option illiquidity and option demand. Therefore, our main results of table 4 and table 5 regarding ATM options survive the additional controls.

Regarding OTM options, in *Panel A* of Table 9, we find that, after controlling for options illiquidity and option demand, BV-SKEW is a strong predictor of returns regardless of the level of MAX. The new variables only offer significant information for low levels of MAX. In sum, option illiquidity and option demand cannot fully explain the cross-sectional variations of lottery stocks and options and the coefficients of MAX and BV-SKEW remain highly significant.

[Table 9 about here.]

5.3 Different Moneyness Intervals

In an additional robustness test we examine whether the results we report in the previous sections depend ou our choice of the moneyness interval for ATM and OTM options. In table 10 we report cross-sectional regressions of option (*Panel A*) and stock (*Panel B*) returns on MAX or BV-SKEW for different intervals, both for ATM and OTM call options. Our analysis includes the group of control variables reported in previous sections. We observe that the main results reported in previous sections are robust to alternative choices of moneyness intervals for ATM and OTM call options.

[Table 10 about here.]

5.4 Alternative Choice of Lottery Options

Next we consider a different approach to select the lottery options. Instead of picking just one option per stock, we form equally-weighted portfolios with all the options with lottery characteristics within the moneyness interval. This way we guard against possible outliers that might be driving our results. The results of this new test are reported in table 11. Despite the fact that this approach might have a smoothing effect that would limit our results, we find that our conclusions remain unchanged, as ATM (OTM) call options of high (low) BV-SKEW (MAX) portfolios render negative and statistically significant returns.

[Table 11 about here.]

5.5 Lottery Stocks without Options

In our previous analysis, we show that optionable stocks do not exhibit significant returns as investors prefer to invest in lottery options. Here, we examine the performance of stocks without options. In general, lottery stocks are small and illiquid; for that reason, we apply a number of filters in the data to control for size. Table 12 shows average excess returns of stocks that are sorted into quantiles based on MAX(10). *Panel A* shows results for portfolios that exclude stocks with prices that are less than $5 or exclude the smallest 10% of stocks. *Panel B* shows results for portfolio sorts based on NYSE breakpoints as well as for stock without options matched with stocks with options based on size. We find that lottery stocks without options offer very negative and statistically significant returns and FF5 alphas. This suggests that skewness-seeking investors trade more heavily stocks with lottery characteristics when an option is not available.

[Table 12 about here.]

6 Conclusions

This paper examines the demand for stocks and options with lottery characteristics. Initially, we investigate the lottery characteristics of stocks and options separately and analyze their performance regardless of the characteristics of the underlying asset. We find that lottery stocks with options do not exhibit significant payoffs while lottery stocks without options remain highly significant. This finding is confirmed by extending our sample of stocks with options to the 70s. This finding offers an out-of-sample test of the previous analysis as the starting point of our data does not affect our results. We also investigate the "lotteryness" of at-the-money or out-of-the money options and find that lottery investors are willing to pay substantial premiums only for the lottery-like characteristics of OTM options.

Next, we analyze the connection between the two markets when both the option and the underlying asset are lotteries. In double sorted portfolios of stocks and options on lottery characteristics of the two markets we find that ATM call options and stocks sorted on the previous month's maximum 10-day daily return (MAX) exhibit lottery payoffs when the ex ante skewness of the options is *high*. On the other hand, there is a substitution between OTM call options and lottery stocks as we show that lottery options tend to be significant when the lottery features of the underlying security are less pronounced (e.g., *low* MAX). This result indicates that investors tend to replace lottery stocks with lottery options when OTM options are available.

To further understand the mechanism through which investors with lottery preferences trade stocks and options with lottery characteristics, we compute order imbalances of the constituents of lottery portfolios. We find that investors are *net sellers* of ATM call options with high MAX and high BV-SKEW and *net buyers* of the underlying securities. We show that this finding is consistent with the notion of covered called strategies. For example, institutional investors (e.g., mutual funds) employ such strategies in order to hedge against adverse movements of the volatile underlying security. On the other hand, we find that gamblers are *net buyers* of OTM call options regardless of the level of MAX without significant trading activity in the underlying security. This finding rationalizing our observation regarding the lottery preferences of gamblers for OTM options and the hedging demand of ATM call options.

We also show that our results are robust to different definitions of moneyness, a number of option trading impediments and alternative selection of stocks.

References

Andrews, D. W. K. (1991). Heteroskedasticity and autocorrelation consistent covariance matrix estimation. *Econometrica 59*(3), 817–58.

Bali, T. G., N. Cakici, and R. F. Whitelaw (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics 99*(2), 427–446.

Barberis, N. and M. Huang (2008). Stocks as lotteries: The implications of probability weighting for security prices. *American Economic Review 98*(5), 2066–2100.

Blau, B., B. Boone, and R. Whitby (2014). Gambling preferences, options markets, and volatility. *Journal of Financial and Quantitative Analysis*.

Bollen, N. P. and R. E. Whaley (2004). Does net buying pressure affect the shape of implied volatility functions? *The Journal of Finance 59*(2), 711–753.

Boyer, B. H. and K. Vorkink (2014). Stock options as lotteries. *The Journal of Finance 69*(4), 1485–1527.

Brunnermeier, M. K., C. Gollier, and J. A. Parker (2007, May). Optimal beliefs, asset prices, and the preference for skewed returns. *American Economic Review 97*(2), 159–165.

Byun, S.-J. and D.-H. Kim (2016). Gambling preference and individual equity option returns. *Journal of Financial Economics 122*(1), 155–174.

Chordia, T., A. Goyal, and N. Jegadeesh (2016). Buyers versus sellers: Who initiates trades, and when? *Journal of Financial and Quantitative Analysis 51*(5), 1467–1490.

Diecidue, E. and J. Van De Ven (2008). Aspiration level, probability of success and failure, and expected utility. *International Economic Review 49*(2), 683–700.

Doran, J. S., D. Jiang, and D. R. Peterson (2012). Gambling preference and the new year effect of assets with lottery features. *Review of Finance 16*(3), 685–731.

Dorn, A. J., D. Dorn, and P. Sengmueller (2014). Trading as gambling. *Management Science*.

Fama, E. F. and K. R. French (1992). The cross-section of expected stock returns. *the Journal of Finance 47*(2), 427–465.

Fama, E. F. and K. R. French (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics 33*(1), 3–56.

Fama, E. F. and K. R. French (2014). A five-factor asset pricing model. *Journal of Financial Economics*.

Fama, E. F. and J. D. MacBeth (1973). Risk, return, and equilibrium: Empirical tests. *The Journal of Political Economy*, 607–636.

Friedman, M. and L. J. Savage (1948). The utility analysis of choices involving risk. *Journal of political Economy 56*(4), 279–304.

Ge, L., T.-C. Lin, and N. D. Pearson (2016). Why does the option to stock volume ratio predict stock returns? *Journal of Financial Economics 120*(3), 601–622.

Harvey, C. R. and A. Siddique (2002). Conditional skewness in asset pricing tests. *The Journal of Finance 55*(3), 1263–1295.

Hu, J. (2014). Does option trading convey stock price information? *Journal of Financial Economics 111*(3), 625–645.

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *The Journal of finance 45*(3), 881–898.

Jegadeesh, N. and S. Titman (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance 48*(1), 65–91.

Kahneman, D. and A. Tversky (1979). Prospect theory: an analysis of decision under risk. *Econometrica 47*(2), 263–291.

Kraus, A. and R. H. Litzenberger (1976). Skewness preference and the valuation of risk assets. *The Journal of Finance 31*(4), 1085–1100.

Kumar, A. (2009). Who gambles in the stock market? *The Journal of Finance 64*(4), 1889–1933.

Lee, C. and M. J. Ready (1991). Inferring trade direction from intraday data. *The Journal of Finance 46*(2), 733–746.

Lee, S. and F. Zapatero (2020). Two reasons to covet social status: a model of status-driven choice. *Working Paper*.

Lehmann, B. N. (1990). Fads, martingales, and market efficiency. *The Quarterly Journal of Economics 105*(1), 1–28.

Lopes, L. L. and G. C. Oden (1999). The role of aspiration level in risky choice: A comparison of cumulative prospect theory and sp/a theory. *Journal of mathematical psychology 43*(2), 286–313.

Markowitz, H. (1952). The utility of wealth. *Journal of political Economy 60*(2), 151–158.

Mitton, T. and K. Vorkink (2007). Equilibrium underdiversification and the preference for skewness. *The Review of Financial Studies 20*(4), 1255–1288.

Natter, M., M. Rohleder, D. Schulte, and M. Wilkens (2016). The benefits of option use by mutual funds. *Journal of Financial Intermediation 26*, 142–168.

Newey, W. K. and K. D. West (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica 55*(3), 703–708.

Ng, K. Y. (1965). Why do people buy lottery tickets? choices involving risk and the indivisibility of expenditure. *Journal of Political Economy 73*(5), 530–535.

Ni, S. X. (2008). Stock option returns: A puzzle. *Available at SSRN 1340767*.

Ni, S. X., N. D. Pearson, A. Poteshman, and J. S. White (2018). Does option trading have a pervasive impact on underlying stock prices? *Available at SSRN 970592*.

Pan, J. and A. M. Poteshman (2006). The information in option volume for future stock prices. *Review of Financial Studies 19*(3), 871–908.

Rapach, D. E., M. C. Ringgenberg, and G. Zhou (2016). Short interest and aggregate stock returns. *Journal of Financial Economics 121*(1), 46–65.

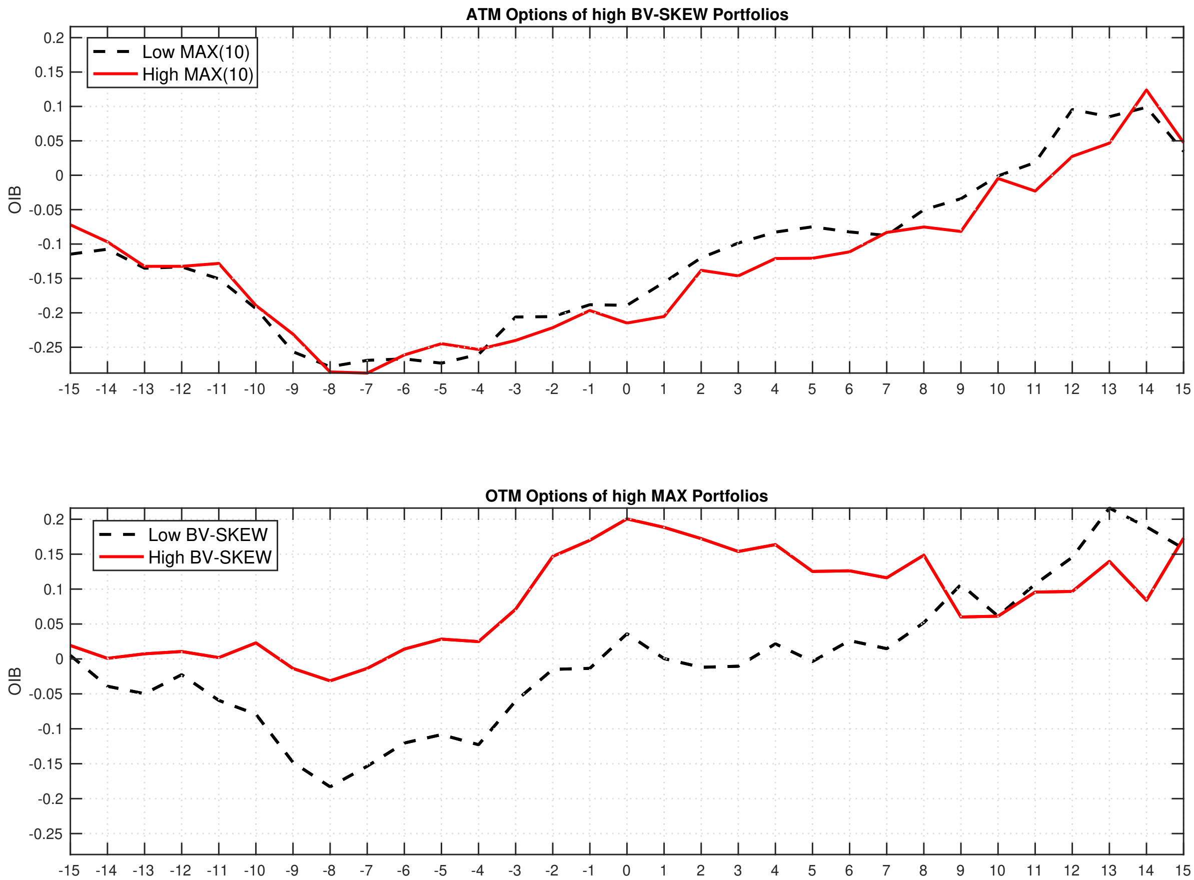
Shefrin, H. and M. Statman (2000). Behavioral portfolio theory. *Journal of financial and quantitative analysis 35*(02), 127–151.

Sorescu, S. M. (2000). The effect of options on stock prices: 1973 to 1995. *The Journal of Finance 55*(1), 487–514.

Tversky, A. and D. Kahneman (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and uncertainty 5*(4), 297–323.

Wang, T. (2015). On the causal effect of option trading on underlying stock pricing. *Available at SSRN 2585680*.

Figure 1. ***Option Order Imbalances Around the Rebalancing Period***



The figure displays order imbalances of ATM options (top graph) and OTM options (bottom graph) sorted on MAX(10) (e.g., stock with the highest maximum daily return over the previous month) (BV-SKEW) within high BV-SKEW (MAX) portfolios. We report equal-weighted average order imbalance from 15 trading days prior to the sorting date until 15 trading days after the rebalancing date. The cross-sectional average corresponds to the average order imbalance of all the assets or interest (e.g., across options) on each day. The data are collected from ISE and contain daily series from January 2006 to December 2016.

Table 1. Univariate Sorts based on MAX Returns

This table presents decile portfolios of stock returns sorted based on the MAX(10) return for the period of July 1963 to January 1996 or for a sub-sample that starts from February 1996 (*Panel A*). *Panel B* reports average returns of MAX(10) portfolios for stocks with and without options. We also report the corresponding alphas of the five-factor Fama and French (2014) model (FF5). Excess returns are expressed in percentage points and all portfolios are value-weighted. *t-stat* represents Newey and West (1987) *t*-statistics corrected for heteroskedasticity and autocorrelation (HAC) using the optimal number of lags as in Andrews (1991). The data is collected from CRSP and contain monthly series from July 1963 to December 2018.

Panel A: All Stocks

	1963-1996				1996-2018			
Decile	Avg Ret	t-stat	FF5 Alpha	t-stat	Avg Ret	t-stat	FF5 Alpha	t-stat
Low MAX	1.186	5.66	0.733	7.44	1.11	4.902	0.52	4.481
2	1.132	5.54	0.664	8.13	1.02	4.505	0.32	4.456
3	1.164	4.52	0.646	6.28	0.81	3.218	0.13	1.614
4	1.103	4.76	0.597	8.27	0.81	2.810	0.06	0.640
5	1.037	4.30	0.585	7.12	0.71	2.126	-0.02	-0.149
6	1.028	3.88	0.591	5.49	0.48	1.171	-0.20	-1.182
7	1.051	3.40	0.651	5.85	0.73	1.660	0.18	1.299
8	0.753	2.26	0.309	2.40	0.51	0.909	-0.03	-0.117
9	0.607	1.64	0.142	1.04	0.32	0.483	-0.08	-0.389
High MAX	-0.265	-0.63	-0.843	-4.39	0.06	0.082	-0.26	-0.718
HML	-1.451	-4.40	-1.576	-7.21	-1.04	-1.54	-0.78	-1.98

Panel B: 1996-2015 (Conditional on Options)

	Stock with Options				Stocks without Options			
Decile	Avg Ret	t-stat	FF5 Alpha	t-stat	Avg Ret	t-stat	FF5 Alpha	t-stat
Low MAX	1.023	4.30	0.410	3.40	1.385	6.92	0.891	6.93
2	1.096	4.88	0.405	4.39	1.058	4.48	0.427	3.02
3	0.871	3.31	0.234	2.13	1.025	3.56	0.322	2.98
4	0.708	2.46	-0.030	-0.30	1.075	3.64	0.410	2.80
5	0.738	2.38	0.058	0.53	0.927	2.97	0.348	2.04
6	0.564	1.47	-0.191	-1.29	0.817	2.01	0.090	0.43
7	0.766	1.64	0.224	1.32	0.814	1.91	0.160	0.88
8	0.601	1.30	0.068	0.47	0.433	0.74	0.099	0.39
9	0.478	0.81	-0.025	-0.13	0.220	0.32	-0.083	-0.30
High MAX	0.361	0.52	0.001	0.00	-0.769	-1.01	-0.903	-2.68
HML	-0.662	-1.07	-0.409	-1.24	-2.154	-2.98	-1.795	-4.67

Table 2. Demand for Stocks with and without Options

This table presents decile portfolios of stock volume sorted based on the MAX(10) return for the period of January 1996 to December 2018 for stocks with and without options (*Panel A*). *Panel B* reports differences in low and high MAX(10) volume deciles of stocks with and without options. We also report the corresponding alphas of the five-factor Fama and French (2014) model (FF5). The volume are expressed in thousand shares and all portfolios are equally-weighted. *t-stat* represents Newey and West (1987) *t*-statistics corrected for heteroskedasticity and autocorrelation (HAC) using the optimal number of lags as in Andrews (1991). The data is collected from CRSP and contain monthly series from January 1996 to December 2018.

Stock Volume				
	Stocks with Options		Stocks without Options	
Decile	Avg Volume	t-stat	Avg Volume	t-stat
Low MAX	3,682,281	12.86	224,762	12.13
2	3,456,455	15.07	215,961	20.46
3	3,312,245	15.77	227,413	23.40
4	3,264,373	16.08	245,307	29.13
5	3,175,537	17.12	261,010	22.89
6	3,092,844	18.57	284,162	16.41
7	2,978,180	19.48	294,651	24.55
8	3,050,328	18.41	342,790	18.38
9	3,146,974	16.20	393,160	17.99
High MAX	3,634,196	10.22	620,622	11.07
HML	-48,085	-0.16	395,860	8.46

Table 3. Options Returns Sorted based on MAX and BV-SKEW

This table presents decile portfolios of options returns sorted based on MAX(10) or BV-SKEW for different intervals of moneyness (e.g., ATM and OTM). We also report the corresponding alphas of the Five-factor Fama and French (2014) model. Option returns are expressed in percentage points and all portfolios are equally-weighted. We compute Newey and West (1987) *t*-statistics corrected for heteroskedasticity and autocorrelation (HAC) using the optimal number of lags as in Andrews (1991). The data is collected from CRSP and OptionMetrics IvyDB database and contain monthly series from January 1996 to December 2018.

Panel A: Option Returns sorted on MAX

	Low	2	3	4	5	6	7	8	9	High	HML	FF5 Alpha
						At-the-money Options						
MAX(10)	11.443	13.098	12.010	9.582	7.092	5.012	4.187	3.100	0.843	-0.572	-12.016	-11.350
	[2.80]	[3.04]	[2.8]6	[2.30]	[1.87]	[1.26]	[1.10]	[0.77]	[0.22]	[-0.14]	[-2.81]	[-3.18]
						Out-of-the-money Options						
MAX(10)	-15.393	-5.890	-14.339	-5.275	-12.735	-15.461	-13.268	-14.461	-15.517	-15.095	0.298	1.314
	[-3.16]	[-0.93]	[-2.73]	[-0.92]	[-2.73	[-2.68]	[-2.23]	[-2.76]	[-2.14]	[-1.98]	[0.04]	[0.18]

Panel B: Option Returns sorted on BV-SKEW

	Low	2	3	4	5	6	7	8	9	High	HML	FF5 Alpha
						At-the-money Options						
BV-SKEW	3.184	5.486	5.895	6.696	6.804	6.678	6.044	5.812	7.365	11.839	8.654	5.507
	[0.98]	[1.49]	[1.64]	[1.79]	[1.71]	[1.65]	[1.47]	[1.47]	[1.71]	[2.75]	[2.72]	[1.73]
						Out-of-the-money Options						
BV-SKEW	-4.016	-3.603	4.735	1.776	-2.038	-9.202	-8.518	-22.051	-27.541	-57.101	-53.085	-48.327
	[-0.63]	[-0.66]	[0.73]	[0.29]	[-0.36]	[-1.66]	[-1.50]	[-4.82]	[-5.20]	[-10.38]	[-6.55]	[-6.13]

Table 4. Stock and Option Returns

This table presents average stock and option returns of portfolios of stock and options double-sorted on 10-day maximum daily stock returns (e.g., MAX(10)) and the Boyer and Vorkink (2014) measure of ex ante skewness of call options (e.g., BV-SKEW) respectively. *Panel A* (*Panel B*) shows option (stock) returns. We report results for independent sorts. We compute Newey and West (1987) t-statistics (in square brackets) corrected for heteroskedasticity and autocorrelation (HAC) using the optimal number of lags as in Andrews (1991). Returns are expressed in percentage points. The data is collected from CRSP and OptionMetrics IvyDB database contain monthly series from January 1996 to December 2018.

Panel A: Option Returns

Lottery Features	Low MAX	2	High MAX	HML^{MAX}	Low MAX	2	High MAX	HML^{MAX}
	At-the-money Options				*Out-of-the-money Options*			
Low BV-SKEW	8.051	4.758	1.347	-6.704	3.518	0.889	-3.741	-7.259
t-stat	[2.29]	[1.35]	[0.32]	[-1.93]	[0.58]	[0.16]	[-0.55]	[-1.16]
2	13.347	6.375	1.494	-11.853	3.729	-5.474	-11.501	-15.230
t-stat	[3.04]	[1.59]	[0.36]	[-3.50]	[0.60]	[-0.94]	[-1.70]	[-2.19]
High BV-SKEW	15.169	8.432	-1.283	-16.452	-26.561	-36.169	-45.365	-18.80
t-stat	[3.26]	[2.01]	[-0.33]	[-5.08]	[-4.93]	[-7.66]	[-9.06]	[-2.90]
$HML^{BV-SKEW}$	7.117	3.674	-2.630		-30.079	-37.058	-41.624	
t-stat	[3.24]	[1.71]	[-0.76]		[-5.40]	[-6.50]	[-7.55]	

Panel B: Stock Returns

Lottery Features	Low MAX	2	High MAX	HML^{MAX}	Low MAX	2	High MAX	HML^{MAX}
	At-the-money Options				*Out-of-the-money Options*			
Low BV-SKEW	0.946	0.682	0.635	-0.311	1.009	0.874	0.874	-0.134
t-stat	[4.19]	[2.37]	[1.33]	[-0.82]	[3.56]	[2.35]	[1.62]	[-0.31]
2	1.023	0.637	0.412	-0.610	0.882	0.942	0.535	-0.347
t-stat	[3.92]	[1.83]	[0.80]	[-1.66]	[3.52]	[2.43]	[0.95]	[-0.79]
High BV-SKEW	1.162	0.692	-0.030	-1.192	1.178	0.448	0.072	-1.106
t-stat	[4.29]	[2.03]	[-0.05]	[-2.21]	[4.25]	[1.01]	[0.12]	[-2.33]
$HML^{BV-SKEW}$	0.216	0.010	-0.665		0.169	-0.426	-0.803	
t-stat	[1.30]	[0.06]	[-1.67]		[0.96]	[-1.65]	[-2.61]	

Table 5. Cross-Sectional Regressions within MAX and BV-SKEW Portfolios

This table presents cross-sectional regressions following Fama and MacBeth (1973) of option returns on lottery stock (e.g, MAX(10)) and option (e.g., BV-SKEW) characteristics. We also take into consideration a number of control variables including log size (Ln(Size)), log stock price (Ln(Price)), institutional ownership (IOR), book-to-market (B/M), debt-to-assets (D/A), turnover, idiosyncratic volatility (IVOL), stock illiquidity (ILLIQ^{Stock}), reversals (REV) and momentum (MOM). The model takes the following form:

$$\text{RX}_{i,t+1} = \gamma_{0,t} + \gamma_{1,i}\text{Lottery}_{i,t} + \gamma'_{2,i}\mathbf{Z}_{i,t} + \varepsilon_{i,t+1}, \text{Lottery} = \text{MAX(10)}, \text{BV-SKEW}$$

where $\text{RX}_{i,t+1}$ denotes the stock or option return of the asset i, MAX(10) is the 10-day maximum return over the previous month and BV-SKEW denotes the ex-ante option skewness estimated as in Boyer and Vorkink (2014). **Z** represents the set of control variables. We also display Newey and West (1987) t-statistics in squared brackets corrected for autocorrelation and heteroskedasticity. The table also shows average of the average adjusted R^2 obtained from the time-series regressions. The data is collected from CRSP and OptionMetrics IvyDB datasets and contain monthly series from January 1996 to December 2018.

Panel A: Option Returns

Lottery Features	Low MAX	2	High MAX	Low MAX	2	High MAX
		At-the-money Options			*Out-of-the-money Options*	
BV-SKEW	3.383	2.378	-0.777	-0.350	-0.010	-0.010
	[2.69]	[1.80]	[-0.39]	[-3.52]	[-2.62]	[-3.17]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R^2	8.25%	8.08%	8.71%	6.62%	6.69%	7.18%
Lottery Features	Low BV-SKEW	2	High BV-SKEW	Low BV-SKEW	2	High BV-SKEW
MAX	-2.066	-4.480	-9.098	-3.994	-12.593	-8.271
	[-1.33]	[-3.08]	[-4.61]	[-1.14]	[-3.21]	[-1.48]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R^2	9.33%	8.17%	7.34%	8.25%	6.54%	6.14%

Panel B: Stock Returns

Lottery Features	Low MAX	2	High MAX	Low MAX	2	High MAX
		At-the-money Options			*Out-of-the-money Options*	
BV-SKEW	0.102	-0.026	-0.098	-0.002	-0.009	-0.019
	[1.75]	[-0.35]	[-0.58]	[-0.70]	[-1.06]	[-1.10]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R^2	12.72%	11.41%	11.60%	14.36%	13.58%	13.87%
Lottery Features	Low BV-SKEW	2	High BV-SKEW	Low BV-SKEW	2	High BV-SKEW
MAX	-0.232	-0.240	-0.497	0.048	-0.309	-0.516
	[-1.46]	[-1.66]	[-3.41]	[0.29]	[-1.86]	[-2.88]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R^2	13.14%	12.70%	13.51%	14.12%	16.23%	15.78%

Table 6. Option Lottery Demand

This table presents average option order imbalances of portfolios of stock and options double-sorted on 10-day maximum daily stock returns (e.g., MAX(10)) and the Boyer and Vorkink (2014) measure of ex ante skewness of call options (e.g., BV-SKEW) respectively.

$$OIMB_{i,t} = \frac{\sum_{i=1}^{N}(Buy_{i,t} - Sell_{i,t})}{\sum_{i=1}^{N} Buy_{i,t} + Sell_{i,t}}$$

where the option order imbalance (OIMB) is defined as the number of opening option trades written on stock i at time t that provides positive exposure to the stock price (e.g., buy calls) less number of option trades that provides negative exposure to the stock price (sell calls as a fraction of the total number of trades at time t. We report time-series averages of order imbalances for all, customers and firms trades. The measures are computed over the holding period (e.g., a month). We report results for independent sorts. We compute Newey and West (1987) t-statistics (in square brackets) corrected for heteroskedasticity and autocorrelation (HAC) using the optimal number of lags as in Andrews (1991). The data is collected from CRSP, OptionMetrics IvyDB and ISE databases and contain monthly series from January 2006 to December 2016.

Panel A: Option Imbalances: All Trades								
Lottery Features	Low MAX	2	High MAX	HML^{MAX}	Low MAX	2	High MAX	HML^{MAX}
		At-the-money Options				*Out-of-the-money Options*		
Low BV-SKEW	-0.055	-0.014	-0.024	0.031	0.150	0.097	0.073	-0.077
	-2.20	-0.63	-0.93	3.03	7.80	4.80	3.66	-4.61
2	-0.082	-0.061	-0.084	-0.002	0.194	0.162	0.137	-0.057
	-3.72	-2.97	-3.58	-0.18	13.08	9.70	7.23	-3.53
High BV-SKEW	-0.050	-0.046	-0.097	-0.047	0.202	0.193	0.149	-0.053
	-2.56	-2.85	-5.36	-5.67	13.78	10.81	7.60	-3.72
$HML^{BV-SKEW}$	0.004	-0.032	-0.073		0.052	0.096	0.077	
	0.35	-2.11	-5.89		2.76	4.74	2.91	
Panel B: Option Imbalances: Customers								
Lottery Features	Low MAX	2	High MAX	HML^{MAX}	Low MAX	2	High MAX	HML^{MAX}
		At-the-money Options				*Out-of-the-money Options*		
Low BV-SKEW	-0.055	-0.025	-0.039	0.016	0.065	0.022	0.008	-0.057
	-2.55	-1.14	-1.54	1.74	3.63	1.12	0.43	-3.30
2	-0.091	-0.080	-0.103	-0.013	0.130	0.096	0.082	-0.048
	-4.75	-4.12	-4.57	-1.44	9.97	6.56	4.35	-2.48
High BV-SKEW	-0.080	-0.080	-0.123	-0.043	0.166	0.153	0.131	-0.035
	-4.62	-5.61	-6.90	-5.34	14.31	9.32	6.61	-2.18
$HML^{BV-SKEW}$	-0.026	-0.055	-0.085		0.101	0.132	0.122	
	-2.55	-3.71	-6.56		5.85	7.10	4.62	
Panel C: Option Imbalances: Firms								
Lottery Features	Low MAX	2	High MAX	HML^{MAX}	Low MAX	2	High MAX	HML^{MAX}
		At-the-money Options				*Out-of-the-money Options*		
Low BV-SKEW	0.000	0.011	0.015	0.015	0.085	0.076	0.064	-0.021
	-0.02	2.08	3.76	3.09	8.73	10.19	11.45	-2.55
2	0.009	0.019	0.020	0.011	0.064	0.066	0.055	-0.009
	1.75	4.73	5.97	1.86	6.08	6.83	7.90	-0.88
High BV-SKEW	0.030	0.034	0.026	-0.004	0.036	0.040	0.019	-0.017
	7.17	7.36	7.52	-0.88	5.59	7.21	2.86	-2.21
$HML^{BV-SKEW}$	0.030	0.023	0.011		-0.049	-0.036	-0.046	
	5.21	4.43	2.80		-5.70	-4.80	-6.33	

Table 7. Stock Ownership of Mutual Funds with Option Holdings

This table presents time series average of stock mutual fund ownership for mutual funds that invest in options during the NSAR semiannual reporting period for portfolios of stocks double-sorted on 10-day maximum daily stock returns (e.g., MAX(10)) and the Boyer and Vorkink (2014) measure of ex ante skewness of call options (e.g., BV-SKEW) respectively. *Panel A* presents summary statistics of mutual funds with option holdings. We report the total number of funds in our sample, the percentage of funds that write options the percentage of funds that buy options as well as the percentage of funds that buy and sell options. *Panel B* shows the time-series average of the ratio of total stock ownership of the constituents of our portfolios over shares outstanding. We focus on the ownership of mutual funds with option trading as reported in semiannual N-SAR filings' items mentioning single stock options on equities (Item 70B). *Panel C* the corresponding time-series average of the stock ownership ratio for the remaining mutual funds that are not involved in option strategies. The data is collected from NSAR SEC filings, Thomson S12, CRSP and OptionMetrics IvyDB databases and contain monthly series from January 1996 to December 2018. The stock mutual fund ownership is expressed in percentage terms.

Panel A: Summary Statistics of Mutual Funds with Equity Options Holdings

	Number of Funds	Written Options Funds Only (%)	Long Options Funds Only (%)	Options Funds Both (%)
Equity Options Holdings	2,351	53.51	21.75	24.74

Panel B: Stock Ownership of Mutual Funds with Equity Options Holdings

Lottery Features	Low MAX	2	High MAX	HML^{MAX}	Low MAX	2	High MAX	HML^{MAX}
	At-the-money Options				*Out-of-the-money Options*			
Low BV-SKEW	0.481	0.547	0.666	0.185	0.599	0.644	0.730	0.131
	[21.36]	[20.77]	[19.48]	[6.64]	[22.70]	[23.14]	[19.31]	[4.88]
2	0.534	0.608	0.714	0.180	0.565	0.663	0.750	0.185
	[23.44]	[21.96]	[22.41]	[7.66]	[22.89]	[22.97]	[19.53]	[6.35]
High BV-SKEW	0.558	0.645	0.729	0.171	0.552	0.664	0.742	0.191
	[22.55]	[22.66]	[19.67]	[6.25]	[24.10]	[21.05]	[18.34]	[6.36]
$HML^{BV-SKEW}$	0.077	0.098	0.063		-0.047	0.020	0.013	
	[6.24]	[6.72]	[3.74]		[-3.09]	[1.30]	[0.59]	

Panel C: Stock Ownership of Mutual Funds without Equity Options Holdings

Lottery Features	Low MAX	2	High MAX	HML^{MAX}	Low MAX	2	High MAX	HML^{MAX}
	At-the-money Options				*Out-of-the-money Options*			
Low BV-SKEW	7.737	8.553	8.532	0.795	8.426	8.633	7.667	-0.759
	[16.93]	[17.81]	[20.51]	[9.08]	[16.61]	[18.06]	[21.14]	[-4.27]
2	8.105	8.581	8.139	0.034	8.341	8.645	7.632	-0.709
	[16.31]	[17.42]	[20.73]	[0.26]	[16.53]	[17.64]	[19.91]	[-4.80]
High BV-SKEW	8.062	8.457	7.667	-0.395	7.901	8.202	7.474	-0.427
	[15.73]	[17.08]	[19.40]	[-2.61]	[17.30]	[17.58]	[18.51]	[-4.52]
$HML^{BV-SKEW}$	0.325	-0.096	-0.865		-0.525	-0.431	-0.193	
	[3.99]	[-1.59]	[-10.15]		[-6.04]	[-7.19]	[-1.97]	

Table 8. Option Listing and MAX Returns

This table presents decile portfolios of stock returns sorted based on the MAX return for stocks without options (*Panel A*) as well as stock with options (*Panel B*). We also report the corresponding alphas of the five-factor Fama and French (2014) model (FF5). Excess returns are expressed in percentage points. *t-stat* represents Newey and West (1987) *t*-statistics corrected for heteroskedasticity and autocorrelation (HAC) using the optimal number of lags as in Andrews (1991). The data is collected from the CBOE, CRSP and Optionmetrics and contain monthly series from June 1977 to December 2018.

Panel A: Stocks without Options

	MAX(5)				MAX(10)			
Decile	Avg Ret	t-stat	FF5 Alpha	t-stat	Avg Ret	t-stat	FF5 Alpha	t-stat
Low MAX	1.343	8.43	0.761	7.52	1.503	8.78	0.926	8.06
2	1.332	7.51	0.630	6.66	1.316	7.38	0.607	6.06
3	1.297	6.42	0.531	6.44	1.411	5.64	0.643	4.27
4	1.315	5.15	0.498	3.15	1.257	5.75	0.491	4.70
5	1.206	4.99	0.488	3.81	1.087	4.71	0.390	3.16
6	1.017	3.48	0.257	2.08	1.008	3.64	0.207	1.51
7	0.891	2.78	0.229	1.53	0.979	3.29	0.277	2.30
8	0.853	2.30	0.446	2.25	0.662	1.76	0.212	1.35
9	0.161	0.37	-0.197	-1.14	0.394	0.93	0.059	0.34
High MAX	-0.708	-1.43	-0.918	-3.87	-0.691	-1.42	-0.879	-3.97
HML	-2.052	-4.51	-1.679	-6.16	-2.194	-4.99	-1.805	-6.83

Panel B: Stocks with Options

	MAX(5)				MAX(10)			
Decile	Avg Ret	t-stat	FF5 Alpha	t-stat	Avg Ret	t-stat	FF5 Alpha	t-stat
Low MAX	1.027	6.67	0.375	4.94	1.067	6.39	0.433	4.28
2	1.061	5.95	0.355	4.80	1.135	6.49	0.423	5.37
3	0.989	5.18	0.290	3.76	1.066	5.53	0.381	4.97
4	1.053	5.08	0.357	3.40	0.991	4.82	0.259	2.82
5	0.975	4.36	0.247	2.24	0.975	4.53	0.309	3.09
6	0.930	3.47	0.276	2.35	0.879	3.41	0.201	1.59
7	1.033	3.69	0.507	4.22	1.021	3.48	0.470	4.01
8	0.995	3.01	0.475	3.25	0.990	3.26	0.471	3.45
9	0.860	2.31	0.431	2.52	0.843	2.27	0.414	2.43
High MAX	0.623	1.46	0.309	1.47	0.650	1.55	0.332	1.55
HML	-0.404	-1.09	-0.066	-0.28	-0.417	-1.14	-0.100	-0.40

Table 9. Cross-Sectional Regressions within MAX and BV-SKEW Portfolios: Option Trading

This table presents cross-sectional regressions following Fama and MacBeth (1973) of option returns on lottery stock (e.g, MAX(10)) and option (e.g., BV-SKEW) characteristics. We also take into consideration a number of control variables including log size (Ln(Size)), log stock price (Ln(Price)), institutional ownership (IOR), book-to-market (B/M), debt-to-assets (D/A), turnover, idiosyncratic volatility (IVOL), stock illiquidity (ILLIQ^{Stock}), reversals (REV) and momentum (MOM). We also control for variable that account for trading impediments in the options market. Specifically, we include a measure of option illiquidity calculated as the option bid-ask spread (ILLIQ^{Options}) and we measure option demand as (Option open interest/ stock volume)*10^3 . The model takes the following form:

$$\text{RX}_{i,t+1} = \gamma_{0,t} + \gamma_{1,i}\ \text{Lottery}_{i,t} + \gamma_{2,i}\text{ILLIQ}^{Options}_{i,t} + \gamma_{3,i}\text{Option Demand}_{i,t} + \gamma'_{4,i}\mathbf{Z}_{i,t} + \varepsilon_{i,t+1}, \text{Lottery} = \text{MAX(10)}, \text{BV-SKEW}$$

where $\text{RX}_{i,t+1}$ denotes the stock or option return of asset i, MAX(10) is the 10-day maximum return over the previous month and BV-SKEW denotes the ex-ante option skewness estimated as in Boyer and Vorkink (2014). **Z** represents the set of control variables. We also display Newey and West (1987) t-statistics in squared brackets corrected for autocorrelation and heteroskedasticity. The table also shows average of the adjusted R^2 obtained from the time-series regressions. The data is collected from CRSP and OptionMetrics IvyDB datasets and contain monthly series from January 1996 to December 2018.

Panel A: Option Returns

Lottery Features	Low MAX	2	High MAX	Low MAX	2	High MAX
	At-the-money Options			*Out-of-the-money Options*		
BV-SKEW	2.928	2.431	-1.999	-0.305	-1.073	-0.960
	[2.14]	[1.79]	[-0.95]	[-3.03]	[-2.53]	[-3.23]
ILLIQ^{Options}	0.067	0.070	0.248	-0.316	-0.179	-0.113
	[0.77]	[1.22]	[2.43]	[-4.41]	[-3.29]	[-1.73]
Option Demand	-0.010	0.001	-0.013	-0.057	-0.055	0.013
	[-0.97]	[0.12]	[-0.93]	[-2.79]	[-2.80]	[0.53]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R^2	9.57%	9.06%	10.10%	7.58%	7.28%	8.62%
Lottery Features	Low BV-SKEW	2	High BV-SKEW	Low BV-SKEW	2	High BV-SKEW
MAX	-1.261	-3.027	-8.888	-2.932	-13.200	-7.941
	[-0.84]	[-2.15]	[-4.65]	[-0.87]	[-3.40]	[-1.53]
ILLIQ^{Options}	0.112	0.180	0.096	0.026	-0.152	-0.265
	[1.45]	[1.86]	[1.35]	[0.37]	[-3.29]	[-3.99]
Option Demand	0.005	-0.019	-0.010	-0.009	-0.040	-0.065
	[0.75]	[-2.85]	[-0.70]	[-0.51]	[-1.54]	[-3.37]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R^2	10.25%	9.45%	8.60%	9.37%	7.57%	7.13%

Panel B: Stock Returns

Lottery Features	Low MAX	2	High MAX	Low MAX	2	High MAX
	At-the-money Options			*Out-of-the-money Options*		
BV-SKEW	0.160	-0.034	-0.119	-0.001	-0.009	-0.020
	[2.41]	[-0.42]	[-0.70]	[-0.31]	[-1.06]	[-1.31]
ILLIQ^{Options}	-0.005	0.002	0.009	-0.001	-0.001	-0.002
	[-2.05]	[0.78]	[1.19]	[-0.59]	[-0.86]	[-0.71]
Option Demand	0.000	0.001	-0.003	-0.002	-0.003	-0.001
	[-0.79]	[1.40]	[-2.23]	[-3.48]	[-3.88]	[-0.34]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R^2	13.44%	12.20%	12.62%	15.40%	14.62%	14.76%
Lottery Features	Low BV-SKEW	2	High BV-SKEW	Low BV-SKEW	2	High BV-SKEW
MAX	-0.195	-0.189	-0.437	0.046	-0.371	-0.355
	[-1.26]	[-1.42]	[-3.19]	[0.29]	[-2.44]	[-2.07]
ILLIQ^{Options}	0.001	-0.002	-0.002	-0.004	-0.001	-0.001
	[0.24]	[-0.53]	[-0.72]	[-2.01]	[-0.76]	[-0.40]
Option Demand	0.000	-0.001	0.000	-0.003	-0.005	-0.002
	[-0.46]	[-1.64]	[0.14]	[-2.80]	[-4.01]	[-1.81]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R^2	13.92%	13.67%	14.35%	15.20%	17.26%	16.92%

Table 10. Cross-Sectional Regressions within MAX and BV-SKEW Portfolios: Different Moneyness Intervals

This table presents cross-sectional regressions following Fama and MacBeth (1973) of option returns on lottery stock (e.g, MAX(10)) and option (e.g., BV-SKEW) characteristics. We also take into consideration a number of control variables including log size (Ln(Size)), log stock price (Ln(Price)), institutional ownership (IOR), book-to-market (B/M), debt-to-assets (D/A), turnover, idiosyncratic volatility (IVOL), stock illiquidity (ILLIQ^{Stock}), reversals (REV) and momentum (MOM). We focus on different moneyness intervals (e.g., [0.94,1.06] or [0.96, 1.04] for ATM options and >1.06 or >1.04 for OTM options). The model takes the following form:

$$\text{RX}_{i,t+1} = \gamma_{0,t} + \gamma_{1,i}\ \text{Lottery}_{i,t} + \gamma'_{2,i}\mathbf{Z}_{i,t} + \varepsilon_{i,t+1}, \text{Lottery} = \text{MAX(10)}, \text{BV-SKEW}$$

where $\text{RX}_{i,t+1}$ denotes the stock or option return of asset i, MAX(10) is the 10-day maximum return over the previous month and BV-SKEW denotes the ex-ante option skewness estimated as in Boyer and Vorkink (2014). **Z** represents the set of control variables. We also display Newey and West (1987) t-statistics in squared brackets corrected for autocorrelation and heteroskedasticity. The table also shows average of the adjusted R^2 obtained from the time-series regressions. The data is collected from CRSP and OptionMetrics IvyDB datasets and contain monthly series from January 1996 to December 2018.

Panel A: Option Returns

Lottery Features	Low MAX	2	High MAX	Low MAX	2	High MAX
		[0.90-1.10]			*>1.10*	
BV-SKEW	1.267	-0.210	-1.133	-0.204	-0.657	-0.969
	[1.51]	[-0.21]	[-0.84]	[-3.10]	[-3.04]	[-2.12]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R^2	7.29%	6.94%	7.45%	11.83%	10.92%	13.33%
Lottery Features	Low BV-SKEW	2	High BV-SKEW	Low BV-SKEW	2	High BV-SKEW
MAX	-1.410	-3.215	-8.278	-6.206	-1.573	-16.634
	[-1.15]	[-2.98]	[-4.20]	[-1.60]	[-0.28]	[-2.40]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R^2	8.26%	7.30%	5.96%	13.01%	11.08%	10.93%

Panel B: Stock Returns

Lottery Features	Low MAX	2	High MAX	Low MAX	2	High MAX
		[0.90-1.10]			*>1.10*	
BV-SKEW	0.094	0.043	0.001	-0.003	-0.006	-0.013
	[2.49]	[0.81]	[0.01]	[-0.76]	[-0.54]	[-0.54]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R^2	11.23%	10.16%	10.09%	19.02%	18.63%	19.44%
Lottery Features	Low BV-SKEW	2	High BV-SKEW	Low BV-SKEW	2	High BV-SKEW
MAX	-0.236	-0.258	-0.412	-0.125	-0.315	-0.386
	[-1.71]	[-2.15]	[-3.24]	[-0.75]	[-1.41]	[-1.42]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R^2	11.49%	11.67%	12.10%	19.87%	20.00%	20.94%

Table 11. Double Sorts: Alternative Selection of Options

This table presents average option returns of portfolios of stock and options double-sorted on 10-day maximum daily stock returns (e.g., MAX(10)) and the Boyer and Vorkink (2014) measure of ex ante skewness of call options (e.g., BV-SKEW) respectively. We consider all available options per stock within the moneyness interval of interest. We compute Newey and West (1987) *t*-statistics (in square brackets) corrected for heteroskedasticity and autocorrelation (HAC) using the optimal number of lags as in Andrews (1991). The data is collected from CRSP and OptionMetrics IvyDB database contain monthly series from January 1996 to December 2018.

Option Returns								
Lottery Features	Low MAX	2	High MAX	HML^{MAX}	Low MAX	2	High MAX	HML^{MAX}
	At-the-money Options				*Out-of-the-money Options*			
Low BV-SKEW	6.764	3.945	1.681	-5.083	5.096	5.626	-2.821	-7.917
	[2.05]	[1.18]	[0.41]	[-1.44]	[0.88]	[1.03]	[-0.46]	[-1.50]
2	13.625	7.048	1.141	-12.484	10.447	0.775	-12.415	-22.861
	[3.17]	[1.76]	[0.28]	[-3.59]	[1.64]	[0.14]	[-1.92]	[-3.05]
High BV-SKEW	20.807	11.611	-1.371	-22.18	-18.089	-25.145	-33.216	-15.13
	[3.96]	[2.58]	[-0.34]	[-5.58]	[-2.99]	[-4.56]	[-4.32]	[-1.75]
$HML^{BV-SKEW}$	14.043	7.666	-3.053		-23.185	-30.771	-30.395	
	[4.89]	[3.26]	[-0.86]		[-4.13]	[-6.50]	[-4.44]	

Table 12. Univariate Sorts based on MAX Returns - Stocks without Options

This table presents decile portfolios of stock returns sorted based on the MAX(10) return. We exclude stocks with price less than 5$ or the smallest 10% of stocks (*Panel A*). *Panel B* reports average returns of MAX(10) portfolios for stocks without options when the sorting is based on breakpoints or based on stocks without options that are matched with stock with options based on size. We also report the corresponding alphas of the five-factor Fama and French (2014) model (FF5). Excess returns are expressed in percentage points and all portfolios are value-weighted. *t-stat* represents Newey and West (1987) *t*-statistics corrected for heteroskedasticity and autocorrelation (HAC) using the optimal number of lags as in Andrews (1991). The data is collected from CRSP and contain monthly series from January 1996 to December 2018.

Panel A: Excluding Small stocks

	Excluding Stocks with Price< \$5				Excluding the smallest 10% of Stocks			
Decile	Avg Ret	t-stat	FF5 Alpha	t-stat	Avg Ret	t-stat	FF5 Alpha	t-stat
Low MAX	1.398	7.32	0.987	6.59	1.357	6.68	0.897	6.56
2	1.362	5.76	0.651	4.23	1.110	4.81	0.428	3.13
3	0.955	3.71	0.326	2.25	0.990	3.59	0.331	2.84
4	1.058	3.67	0.361	2.30	1.021	3.35	0.389	2.58
5	1.030	3.57	0.313	2.61	0.933	2.85	0.254	1.58
6	0.911	2.79	0.315	1.68	1.044	3.26	0.404	2.29
7	0.937	3.05	0.342	1.72	0.840	1.92	0.177	1.06
8	0.704	1.74	0.042	0.22	0.320	0.64	-0.183	-0.78
9	0.659	1.36	0.164	0.73	0.567	0.89	0.276	0.94
High MAX	-0.186	-0.29	-0.403	-1.27	-0.445	-0.61	-0.736	-2.65
HML	-1.585	-2.61	-1.390	-3.59	-1.802	-2.71	-1.633	-5.13

Panel B: Breakpoints and Matched Firms

	Including Breakpoints				Stocks matched based on Size			
Decile	Avg Ret	t-stat	FF5 Alpha	t-stat	Avg Ret	t-stat	FF5 Alpha	t-stat
Low MAX	1.479	6.76	1.055	6.26	1.354	6.94	0.938	5.90
2	1.249	5.01	0.580	4.04	1.296	5.50	0.659	4.56
3	1.122	4.05	0.415	2.70	0.907	3.21	0.207	1.30
4	1.049	3.52	0.450	3.03	0.875	2.78	0.272	1.43
5	1.154	3.85	0.559	3.47	0.868	2.71	0.235	1.10
6	0.979	3.18	0.343	2.72	0.913	2.82	0.289	1.49
7	1.052	3.11	0.414	2.00	0.692	1.78	0.057	0.24
8	1.027	2.78	0.349	2.17	0.794	1.67	0.200	0.91
9	0.779	1.90	0.154	0.73	0.301	0.54	0.076	0.24
High MAX	0.071	0.11	-0.235	-1.01	0.053	0.07	-0.238	-0.61
HML	-1.408	-2.46	-1.290	-4.34	-1.300	-1.72	-1.176	-2.59

Internet Appendix to

"Demand for Lotteries: The Choice Between Stocks and Options"

by

Ilias Filippou   Pedro Garcia-Ares   Fernando Zapatero

(Not for publication)

Appendix A: Variables description

In this section we provide a detailed description of the variables employed in the paper. The first subsection describes the main option variables and the second analyzes the stock variables.

1.1 Option Characteristics

Ex-ante skewness: We follow Boyer and Vorkink (2014) (equations 1 through 4) in order to estimate ex ante skewness. We obtain estimates of the expected returns and volatility for every underlying stock in our sample. To this end, we employ daily returns from the CRSP daily database over the previous 3 months (we compute 3 months of data immediately prior to our formation date). Our results remain robust after considering 6 months instead of 3 months of daily data.

Option order imbalance: Following Bollen and Whaley (2004) and using ISE data we compute time-series averages of mean order flows imbalances for each option i over a 3-week period, computed as the difference between its buying and selling orders during that period divided by the total amount of buying and selling orders over the same period. We also compute disaggregated order imbalances (e.g., order imbalances of firms and customers).

Call Premium (CALL PRE): Average of bid and ask prices of the options at the end of each month.

Moneyness (X/S): We define the moneyness of an option as the ratio of the strike price of the option divided by the price of the underlying asset.

Option Iliquidity ($(\text{ILLIQ}^{Options})$) : We measure liquidity for each option as the ratio of the bid-ask spread to its mid-price during the rebalancing period (e.g last trading day of the month).

1.2 Stock Characteristics

MAX(10): Following Bali et al. (2011) we define MAX(k) of stock i in month t as the maximum k-day daily return. We compute the average of the k =5 and 10 highest daily returns of each stock within the month.

Stock order imbalance: We apply the Lee and Ready (1991) algorithm to classify transactions as either a buy or a sell. Chordia, Goyal, and Jegadeesh (2016) offer a detailed discussion on the implementation of the Lee and Ready algorithm as well as the alleviation of potential concerns regarding the use of this method for daily and monthly estimates.

Idiosyncratic skewness (ISKEW): Following Harvey and Siddique (2002), we define the idiosyncratic skewness of stock i in month t as the skewness of daily residuals during the previous 3 months.

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_i(R_{m,d} - r_{f,d}) + \gamma_i(R_{m,d} - r_{f,d})^2 + \nu_{i,d}, \tag{5}$$

where $R_{i,d}$ is the stock return i on day d, $R_{m,d}$ is the market return and $r_{f,d}$ is the risk-free rate. Thus, the idiosyncratic skewness of stock i in month t as the skewness of the daily residuals ($\nu_{i,d}$) obtained from the model above, over the previous 3 months.

Idiosyncratic Volatility (IVOL): We estimate the monthly idiosyncratic volatility of each stock at month t as the standard deviation of daily residuals in month t obtained from the Fama and French (1993) 3-factor model:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_{1,i}(R_{m,d} - r_{f,d}) + \beta_{2,i}HML_d + \beta_{3,i}SMB_d + \varepsilon_{i,d}, \tag{6}$$

where $R_{i,d}$ is the stock return i on day d, $R_{m,d}$ is the market return and $r_{f,d}$ is the risk-free rate. In addition, HML and SMB represent the zero-cost portfolios that are related to the high-minus-low book-to-market and the small-minus-big size factors. Thus, we define the idiosyncratic volatility (IVOL) of stock i in month t as the standard deviation of the daily residuals obtained from the model above: $IVOL_{i,t} = \sqrt{var(\varepsilon_{i,d})}$.

Stock Illiquidity (ILLIQ^{Stock}): We measure liquidity for each stock as the ratio of the bid-ask spread to its mid-price during the rebalancing period (e.g last trading day of the month).

Turnover: We compute monthly stock turnover as the number of shares traded in a month divided by the outstanding shares at the end of the month.

Size: Firm size is defined as the market value of equity (that is stock price times shares outstanding at the end of the previous month)

Book-to-market (B/M): Following Fama and French (1992) we compute a firm's book to market ratio at the end of each month (book values are lagged 6 months while we consider the most recent market values in order to obtain the ratios).

Debt-to-assets (D/A): This ratio is computed as the ratio of the the book value in moth t of total debt –which is defined as long term debt plus debt in current liabilities– over the book value of total assets.

Institutional Ownership (IOR): Institutional ownership is computed as the percentage of shares outstanding reported by 13F institutions at the end of each month. Institutional holdings are reported on a quarterly basis. We assume that the holdings remain constant during the quarter in order to compute our monthly measure.

Momentum (MOM): Following Jegadeesh and Titman (1993), we define the momentum variable as the cumulative return on the stock of the months $t-12$ until $t-2$. The main reason for skipping the most recent month is to avoid short-term reversals.

Short-term reversals (REV): As in Jegadeesh (1990) and Lehmann (1990), the short term reversal is obtained by allocating equities into portfolios based on their previous month return.

Appendix B: Filters of the option data

Consistently with the literature we apply a number of filters in the data in order to ensure tradability. Our screening procedure is in line with Boyer and Vorkink (2014) and Byun and Kim (2016). Specifically, we start with daily options data that are collected from the Ivy OptionMetrics. We exclude all observations that demonstrate at least one of the option features below:

1. Settlement: A different than zero "settlement flag" obtained from the OptionMetrics dataset.

2. Abnormal bid and ask difference: the bid-ask spread is negative or exceeds \$5.

3. Extreme price: The option's price is less than 50% of the intrinsic value or it exceeds by more than \$100 the intrinsic value.

4. Abnormal implied volatility (IMP VOL): Implied volatility is less than zero or missing.

5. Abnormal delta (Δ): The Δ is below -1, above +1, or missing.

6. Zero or missing open interest.

7. No trading (e.g, the volume is missing on the rebalancing date).

We merge the Ivy OptionMetrics data with the CRSP stock data as well as the ISE data. Any erroneous matches in the merging procedure are also excluded from our analysis.