Demand for Lotteries: the Choice Between Stocks and Options

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Abstract

We show that the availability of options for retail investors displaces lottery stocks. We also find that investors are willing to pay substantial premiums only for the lottery characteristics of deep-out-of-the-money options. Additionally, at-the-money lottery options and lottery stocks are complements. Finally, deep-out-of-the-money options replace lottery stocks when lottery stocks are not available, therefore they are substitutes. These results allow us to interpret order imbalances in lottery stocks and lottery options as gamblers tend to be net buyers of lottery options when DOTM options are available. In addition, lottery investors are net sellers of both ATM lottery options and stocks attached to ATM lottery options.

Keywords: Lottery-payoffs, Option Trading, lottery stocks.

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1 Introduction

We characterize and analyze the relationship between trading patterns of *lottery stocks* and *lottery options*. The notion of investments in securities with lottery characteristics –low price, large right skewness and negative expected return– has been discussed in the literature for a long time (see for example, Markowitz, 1952). Over the last decade, a fast growing literature has studied investments in securities with lottery characteristics, in particular, lottery stocks (e.g., Kumar, 2009; Bali, Cakici, and Whitelaw, 2011) and lottery options (e.g., Boyer and Vorkink, 2014; Byun and Kim, 2016). This paper is the first attempt to study their interaction and the investment patterns of investors seeking lottery securities.

The motivation to invest in securities with lottery properties has been discussed in the literature –Kumar (2009) is one of the recent papers on the topic– and we take it as given. Contingent on investing in lottery securities, the analysis so far has focused either on stocks or on options, but has not considered the interaction between the two –Byun and Kim (2016) sort out at-the-money options based on the characteristics of the stocks on which they are written, but do not compare their findings of investment in lottery options with investments in the corresponding stocks. Our goal is to study the relationship between trading across both categories. We show that lottery stocks and lottery options sometimes are substitutes, sometimes are complements. In particular, we document that overtime trading in lottery options replaces trading in lottery stocks. However, we find some complementary trading between lottery stocks and at-the money calls when both the option and the underlying asset exhibit lottery features. We also find that investors hold lottery deep-out-of-the-money options when the stocks do not display lottery characteristics –they substitute lottery stocks.

An important problem in the study of lottery securities is their characterization as such. In particular, it does not seem possible to estimate ex ante skewness with any degree of accuracy, based on historical data. The literature on lottery securities has devoted a substantial amount of effort to address this issue. With respect to lottery stocks, Bali et al. (2011) show that stocks with the highest daily return over the previous month are treated by investors as lottery stocks. In particular, they show that there is a statistically significant return differential between stocks with the highest maximum daily return over the previous month compared with stocks with the lowest maximum daily return –this is also extensive to the highest two- to five-day returns. This indicates that investors are willing to overpay for these securities, in the hope that they will exhibit a high return, as a lottery investor would do. We follow this approach in our selection of lottery stocks.

For investors with gambling preferences, in principle, equity options are an attractive choice because the statistical properties they inherit from the underlying stocks are compounded by the leverage implicit in them. However, as in the case of stocks, it is not obvious how to assess the ex-ante skewness of equity options. Boyer and Vorkink (2014) show that it is possible to evaluate the lottery properties of equity options depending on their moneyness and the volatility of the underlying stock. In particular, they assume that the price of the underlying stock is lognormally distributed –therefore ignoring possible skewness in stock returns– and compute the ex-ante skewness of the option return –they show that their lognormality assumption is conservative and their conclusions are stronger if stock returns display skewness. As in the case of stocks, they show that the average risk-adjusted return on options with high ex ante skewness is lower than for options whose returns have low skewness. Again, this is an indication of preference for skewness on the part of some investors who are willing to overpay for these options and, therefore, bring down their average returns.

In this paper we study the relation between trading of lottery stocks and lottery options. We 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 daily returns over these time periods. For options, the data with all the details we need is available from 1996 and that is what we use. To determine what options are in the lottery category we use the method of Boyer and Vorkink (2014) we sketched before.

Our first analysis establishes the tone for all the results of the paper. We sort out stocks in deciles in terms of their "lotteryness," that is, from highest to lowest maximum 10-day returns over the previous month –we repeat it with 5-day returns. We first consider stocks from 1963 to 1996, the first date for which we have options data available (at that point option markets have grown to be easily accessible by 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, is not significant anymore. We then breakdown the sample of stocks between those with options written on them and those without. We document that the difference in result 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 by other exercises– is that investors with gambling preferences chose options over stocks, when options are available.

Next we allocate options into deciles based on their option lotteryness from low to high ex-ante skewness. We study the returns of these lottery portfolios for at-the-money (ATM), out-of-the-money (OTM) and deep-out-of-the-money options (DOTM). First, we observe that regardless of the underlying asset ATM and OTM options do not exhibit lottery characteristics. In contrast, we find that investors are willing to pay substantial premiums for the lottery-like characteristics of DOTM, as their spread portfolio yields very negative and statistically significant returns. In fact, investors are willing to give up returns of more than 60% per month for the lottery potential of DOTM options. In sum, lottery seekers prefer DOTM options, arguably because they are cheaper and their implicit leverage magnifies their lottery-like features.

In the previous analysis, we consider lottery features of the stock and option markets separately. Next, we perform a double-sort analysis of lottery stocks and lottery options in order to examine further the relationship between the two strategies when both stocks and options exhibit lottery characteristics. We find that both, stock returns of lottery stocks and option returns of the underlying at-the-money call options sorted on MAX(10) render highly negative and statistically significant spread portfolios when the BV-SKEW is *high*. This pattern illustrates a feedback effect between lottery stocks and the corresponding ATM lottery options as both strategies exhibit lottery features (e.g., complementarity). More precisely, ATM options sorted on MAX tend to be overvalued creating subsequent overvaluation in the stock market. On the other hand, only the option returns of spread portfolios of deep-out-of-the money call options tend to be negative and statistically significant when the lotteryness of the stocks is is *low* (e.g., substitution). Thus, investors tend to replace lottery stocks with lottery options when deep-out-of-the-money options are available.

To corroborate the previous results, we study the order imbalance in both lottery stocks and lottery options. This measure considers buy and sell orders of lottery stocks and options conveying the informational role of transactions volume in such strategies. If gamblers have an alternative lottery choice from which they can profit more, then their trading may have important implications not only for the prices of the lottery asset they invest in but also for the price of the alternative choice. In fact, the transactions of lottery options transmit information not only for the prices of lottery options but also for the price of lottery stocks as the trading activity might be shifted from one asset to the other.

In particular, we compute the time-series average of the median trade imbalances from the time of portfolio formation at the end of the month until maturity of the call options, three weeks later –in all of our analysis we work with options with three weeks left to maturity to avoid time-to-maturity heterogeneity. In fact, we are interested in retail investors, since preference for gambling is more likely to be found in this group. We find that after the time of portfolio formation gamblers are net sellers of at-the-money calls of the lottery stocks across BV-SKEW portfolios, consistent with the fact that they had accumulated them based on the 10-day returns in the previous month. This finding indicates a downward price pressure on such assets until their expiration. This is also an indication that the lotteryness of the underlying asset makes the associated ATM options overvalued. We also observe a similar pattern for lottery stocks with high BV-SKEW. Specifically, gamblers tend to be net sellers of lottery stocks with available lottery ATM options creating a feedback effect as the selling pressure in the options market is also translated into the corresponding selling of lottery stocks. Thus, the MAX strategy becomes negative and statistically significant. On the other hand, we observe that gamblers are, on average, net buyers of DOTM lottery options across different levels of MAX and net sellers of the corresponding stocks. In addition, there is no significant trading activity for lottery stocks indicating that gamblers substitute lottery stocks with lottery options when DOTM lottery options are available.

We further compute the correlation of order imbalances and find statistically significant negative correlation between the order imbalance of lottery stocks and lottery options, regardless of whether they are at-the-money or out-of-the-money. This finding confirms that overtime gamblers tend to substitute lottery stocks with lottery options. We also show that the substitution is more pronounced in the group of small trades (e.g., retail traders who place option orders of less than 100 contracts each, through a broker).

We perform a number of robustness tests that confirm our results. We also perform Fama and MacBeth (1973) two pass regressions of the option returns as well as panel regressions of order imbalances and the lottery characteristics of interest. This allows us to control for a number of factors. We also study deviations from put-call parity as in Byun and Kim (2016). They give us an idea of the overpricing driven by the preference for gambling. As in Ofek, Richardson, and Whitelaw (2004), we study short interest to further analyze deviations from put-call parity. Following Blau, Boone, and Whitby (2014) we investigate the role of speculative option trading (proxied by call ratios) in call options sorted based on the previous month lottery characteristics of stocks and options. Overall, all the robustness tests confirm our previous results.

The rest of the paper is organised as follows: section 2 provides a literature review, section 3 describes the data and portfolios construction. Section 4 discusses the empirical results. Section 5 includes different determinants of lottery assets. Section 6 provides a broad range of robustness and other specification tests and section 7 concludes.

2 Related Literature

In this section we provide a brief review of the studies that analyze the behavior of assets with lottery-like payoffs.

Lottery Options. Wang (2015) finds that option trading could cause higher overpricing of the underlying asset. Our work is also closely related to Blau et al. (2014) who 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. They relate this finding with the speculative derivatives trading theory of Stein (1987) and show that speculative call options increase the volatility of the underlying stock leading to destabilised prices. On the other hand, Byun and Kim (2016) find that at-the-money options tend to be more overvalued as the maximum past daily returns (MAX) of the underlying asset increases rendering lower future returns. Specifically, they show that buying call options written on the most lottery-like stocks underperform similar call options written on the least lottery-like stocks by as much as 20% per month.

In addition, Boyer and Vorkink (2014) construct an ex ante skewness measure (BVSKEW) for option returns and document a negative relation between option's lottery-like characteristics and returns. In particular, they find that total skewness, rather than co-skewness, is negatively related to average option returns. This finding suggests that investors can accept losses from options that exhibit lottery payoffs. We deviate from Byun and Kim (2016) and Boyer and Vorkink (2014) as we study separately the dynamics of stocks and options with lottery-type payoffs and find that lottery options tend to replace lottery stocks.

Lottery Stocks. The behavior of the investors that are "allured" by lottery stocks is motivated by the cumulative prospect theory of Tversky and Kahneman (1992) and Barberis and Huang (2008). Particularly, investors hold securities with negative returns because they exhibit lottery-like attributes and right-tailed payoffs leading to underdiversification in equilibrium. Barberis and Xiong (2012) explain the demand for lottery stocks on the bases of the realization utility model based on which the investors realize gain (losses) of their stocks meaning positive (negative) realization utility. Bali et al. (2011) identify a statistically and economically significant relation between maximum past daily returns and expected stock returns. Particularly, they show that investors are attracted by lottery-like stocks – equities that exhibit very positive excess returns with low probability. These results are robust to a number of control variables, including idiosyncratic volatility and skewness.

However, investor's sentiment can partially explain this phenomenon (Fong and Toh, 2014). Eraker and Ready (2015) show that over-the-counter stocks exhibit lottery-like behavior as most of them perform poorly while a small number of stocks do unexpectedly well. The authors show that these stocks are attracted by investors who seek right-skewed payoffs. Bali, Brown, Murray, and Tang (2014) investigate the betting against beta phenomenon of Frazzini and Pedersen (2014) – a highly profitable strategy that it is based on a long (short) position in low (high)-beta stocks. The authors show a strong link between the aforementioned strategy and the demand for lottery-like stocks that emerges from the increased lottery demand price pressure on *high*-beta stocks. Kumar (2009) stresses the role of the socioeconomic attributes of the investors in their tendency to gamble. Dorn, Dorn, and Sengmueller (2014) find a negative relation between jackpot and trading of stocks with lottery-like payoffs. 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 other months of the year.

One plausible explanation of the increasing demand for lottery stocks is associated with their distribution properties. Specifically, lottery stocks are usually small, illiquid stocks with positive skewness. Thus, many studies document that investors who trade lottery stocks, seek right skewed assets for their portfolios. Green and Hwang (2012) suggest that initial public offerings with higher skewness demonstrate larger returns on the first day with subsequent negative returns in the long run. Barber, Lee, Liu, and Odean (2009) show that the propensity to gamble determines a substantial part of the excessive trading of individual investors in Taiwan. Excessive trading is also related to other behavioral aspects of individual investors such as overconfidence (see e.g., Odean, 1998; Barber and Odean, 2000, 2001; Grinblatt and Keloharju, 2009) as well as status (Hong, Jiang, Wang, and Zhao, 2014) and entertainment or gambling (Dorn and Sengmueller, 2009) attributes.

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 August 2015. 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. The availability of the data is from January 1996 until August 2015. In our analysis, we mainly focus on at-the-money (ATM), out-of-the money (OTM) and deep out-of-the money options (DOTM) 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 underlying asset (i.e. S) and the strike price of the option (i.e. X). Then, we select only one option per underlying asset that satisfies our criteria. Specifically, we define as ATM options those options with moneyness between 0.90 and 1.10 (i.e. $0.90 < X/S < 1.10$) and it is close to 1, the OTM options have moneyness between 1.00 and 1.10 (i.e. $1.00 < X/S < 1.10$) and it is closer to 1.1 (we select only those options with moneyness higher than the median) and deep OTM options exhibit the highest moneyness ratio above 1.10 (i.e. X/S>1.10).

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).

Stock Order Imbalances. We obtain order imbalance data from the TAQ database which reports intraday trade volume and prices for each stock. We then use the Lee and Ready (1991) algorithm to classify transactions as either a buy or a sell by looking at prices above or bellow the quote midpoint. This is based on the fact that seller-initiated trades tend to execute at a lower price than buy-initiated trades. Following Chordia, Goyal, and Jegadeesh (2016), we define stock order imbalances as:

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

where $\text{Buy}_{i,t}$ ($\text{Sell}_{i,t}$) represents the number of buyer (seller)-initiated transactions for stock i at time t. The denominator represents the total number of trades. Thus, a positive (negative) value of the order imbalance implies that investors are, on average, net buyers (net sellers) of the stocks of interest. We focus on the number of trades rather than the number of shares traded so as to assign the same weight to all trades regardless of the size. In this way small and large trades will have the same weight. The main reason for this approach is that lottery trading is more concentrated to small traders rather than institutional investors. In particular, we aggregate the trade-level imbalances for each stock from the time of portfolio formation at the end of the month until maturity of the call options, three weeks later. This also alleviates concerns about the accuracy of the Lee and Ready (1991) algorithm classifying the side that initiated a particular trade.

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 and but is only available for a part of our sample period from 2006-2015. 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 August 2015. We focus on disaggregated trades for small customers (e.g., retail traders who place option orders of less than 100 contracts each, through a broker) and firms (e.g., a market participant who place an order for her own account). We follow Bollen and Whaley (2004) and we define option order imbalances as:

$$OIMB_{i,t} = \frac{\sum_{i=1}^{N} \Delta Buy_{i,t} - \Delta Sell_{i,t}}{\sum_{i=1}^{N} Buy_{i,t} + Sell_{i,t}} \tag{2}$$

where $\text{Buy}_{i,t}$ ($\text{Sell}_{i,t}$) represents buyer (seller)-initiated transactions and is defined as Open $\text{Buy}_{i,t}$+Close $\text{Buy}_{i,t}$ (Open $\text{Sell}_{i,t}$+Close $\text{Sell}_{i,t}$) for option i at time t. In other words, a positive option order imbalance means that investors tend on average to buy (sell) call (put) options. Similarly, a negative option order imbalance shows that traders assign upward price pressure on put options and 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 August 2015.

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.

Shorting Fees. As in Drechsler and Drechsler (2014) we provide a proxy of shorting fees that captures the shorting interest as a function of the lending supply estimated based on the institutional ownership. In particular, the shorting fee is defined as the ratio of the aggregated short interest in an equity to its institutional ownership (e.g., the total number of shares held by institutions). We employ short interest data from Compustat in order to derive a proxy for firm-level shorting fees by estimating a ratio of the mid-month short interest in a stock to the number of shares of the stock of interest held by 13F institutions. We convert the quarterly institutional holdings to monthly observations by keeping the holdings constant within each quarter. In this way, we assume that the institutional holdings change on a quarterly bases and remain constant otherwise.

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

$$RX^{c}_{j,t:T} = \frac{\max(0, S_{j,T} - X_j)}{0.5(P^{ask}_{c} + P^{bid}_{c})} - 1, \quad (3)$$

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 Stock and Option 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.[1]

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.[2] 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.

4 Empirical Results

This section studies the relationship between lottery stocks and lottery options. First, we investigate the two strategies separately and analyze their performance. Next, we examine the interaction between the two strategies by allocating options and stocks into portfolios based on MAX –for lottery stocks– and BV-SKEW –for lottery options. In other words, we investigate the lottery choice when both stocks and options are lotteries.

[1] 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.

[2] 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.

4.1 Univariate Sorts

Lottery Stocks. Firstly, 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 five-day (MAX(5)) or 10-day (MAX(10)) maximum daily return. *Panel A* of Table 1 reports results from July 1963 to January 1996 while *Panel B* displays MAX returns from January 1996 to August 2015. January 1996 is not only the first date options data is available but also a point in time at which options had become available to retail investors.[3] Our objective is to understand trading in lottery stocks when options had become available as a possible substitute. In particular, if investors were still willing to pay a premium for lottery stocks.[4] Indeed we find that while 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 (*Panel B*).

More precisely, we report excess returns of decile portfolios of stocks sorted based on previous month MAX return. 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-factor Fama and French (2014) model, consistent with lottery stocks being overpriced because investors are willing to pay a premium for them. All portfolios are value-weighted.[5]

[3] 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-August 2015) are similar to *Panel A* and they are available upon request.

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

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

Yet, this changes when we examine the period from 1996 until the end of the sample. In particular, we observe in *Panel B* that the return of the spread portfolio becomes insignificant. This indicates 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. Another reason might be the fact that lottery assets in the options market become more attractive than in the stock market due to other factors (e.g., increases in illiquidity) and vice versa. We will test this possibility in a later section.

Panel C 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. Notably, the MAX strategy is significant for stocks without options for both MAX(5) and MAX(10) portfolios. We will offer later potential explanations of the significance of the MAX strategy when considering stocks without options.[6]

[Table 1 about here.]

Lottery Options. In the same vein, we allocate options into decile portfolios based on their ex-ante skewness (BV-SKEW). Boyer and Vorkink (2014) construct an ex ante skewness measure (BV-SKEW) for option returns and demonstrate a negative relation between option's lottery-like characteristics and returns, that is, investors are willing to pay a premium to hold these options. In other words, BV-SKEW is an indicator of option lotteryness. Since our main focus is on one option per stock, we select options from three different moneyness

[6] In what follows, we will focus on MAX(10) portfolios but we have verified that the results for MAX(5) portfolios are similar.

intervals that expire the following month.[7] Specifically, we denote as *at-the-money* (ATM) options those that have moneyness levels around 1 (i.e., $X/S \rightarrow 1$); in particular, we choose the interval between 0.90 and 1.10.[8] Likewise, the options we denote *out-of-the-money* (OTM) exhibit moneyness close to 1.10 within the interval of 1-1.10.[9] Options with moneyness above 1.10 (i.e. $X/S > 1.10$) are classified as *deep-out-of-the-money* (DOTM) options.

Table 2 presents mean returns of decile portfolios of options sorted on ex-ante skewness (BV-SKEW). We include alphas of the Fama and French (2014) five-factor model only 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). Options returns are equally-weighted.

We note that, unconditionally –i.e., regardless of their underlying–, ATM options do not exhibit lottery characteristics in comparison to DOTM options, which have higher leverage, (e.g., Boyer and Vorkink, 2014; Ni, 2008). More precisely, lottery seekers prefer DOTM options to ATM options as they are cheaper and their implicit leverage magnifies the lottery attributes of the underlying asset. We find, in line with the literature, that investors are willing to pay a premium only for DOTM, as their spread portfolios render negative and statistically significant returns. Finally, OTM options are not affected by BV-SKEW as the return of the spread portfolio is insignificant.

[Table 2 about here.]

[7] We find similar results when considering an equally-weighted average of options within the interval of interest. The results are available upon request.

[8] Byun and Kim (2016) follow a similar approach.

[9] We sort all the available options within the interval 1-1.10 and we pick those that have the highest moneyness if and only if their moneyness level is larger than the median. In this way, we avoid any overlapping with ATM options as we obtain only options with moneyness closer to 1.10.

4.2 Bivariate Sorts

In this section, we perform a double-sort analysis of lottery stocks and lottery options in order to examine further the relationship between the two strategies. In particular, we ask if the mispricing of DOTM options reported in the previous section depends on whether both the option and the underlying stock exhibit lottery characteristics. In addition, we examine if the MAX strategy is significant conditional on the lotteryness of the attached options. Thus, we double-sort options and stocks, independently, into three portfolios based on MAX and BV-SKEW and vice versa. In the Internet Appendix, we report results of dependent sorts.

Our goal is to attain a better understanding of the MAX strategy and investigate the source of insignificance of lottery stock spread portfolios when the stocks *have* options written on them. To this end, we ask whether the lotteryness of the options written on lottery stocks affects the overvaluation of the latter (e.g., Kumar, 2009; Bali et al., 2011). Conversely, we examine the stock lotteryness –measured through MAX– on options with and without lottery characteristics. For example, Byun and Kim (2016) show that at-the-money options tend to be more overvalued as the MAX of the underlying asset increases –so that the lotteryness of stocks and at-the-money options seem to move in the same direction.

At-the-money Options. *Panel A* of table 3 demonstrates average option returns sorted based on BV-SKEW and MAX. We explore whether the insignificant payoff of ATM options sorted on BV-SKEW (as reported in table 2) changes when we consider different levels of MAX. We find that ATM options sorted by the standard characterisctics of lottery options do not behave as actual lottery securities, regardless of the lotteryness of the underlying asset. In contrast, we corroborate the result of Byun and Kim (2016) that the returns of ATM options sorted on MAX are always negative and significant. We also find that their prices tend to be more overvalued as the BV-SKEW increases. Specifically, lottery investors give up average returns of about 16% per month for the lottery potential offered by lottery options (e.g., high BV-SKEW) when the underlying asset is also a lottery. This loss is more that two times higher than the corresponding return of the low BV-SKEW portfolios. Namely, ATM options do not behave as lotteries (e.g., as we show in table 2) unless the underlying asset is a lottery.

Panel B exhibits the corresponding average stock returns of BV-SKEW and MAX-sorted portfolios. In particular, we find that BV-SKEW spread portfolios of stocks are negative and significant only for high MAX portfolios. This could reflect that the overvaluation of high MAX portfolios is more pronounced for stocks with positive ex-ante skewness as investors recognize their high lottery potential. In addition, we observe that the MAX strategy is highly significant for stocks with high BV-SKEW ATM call options. This indicates that not only the ATM options with high ex-ante skewness are overvalued but also that the underlying stocks become overpriced, maybe due to the transmission of the information from the forward-looking option market. In other words, we observe a potential feedback effect because the overvaluation of ATM options –caused by the lottery characteristics of the underlying asset- generates an upward price pressure on the underlying asset rendering a highly negative and statistically significant stock returns. This argument is consistent with information-based models which show that option order flow exhibit strong predictive ability for the underlying stock (e.g., Easley, O'hara, and Srinivas, 1998; Pan and Poteshman, 2006). Specifically, Hu (2014) shows the price impact in the stock market generated by the option market maker who is moving to the stock market in order to hedge away the exposure to the underlying asset. Thus, there is *complementarity* between lottery stocks and lottery options as lottery investors tend to invest in both assets.

Out-of-the-money Options. Table 3 also reports results for OTM options sorted on BV-SKEW and MAX. Here, we observe that option returns of BV-SKEW spread portfolios are not statistically significant regardless of the level of MAX. Similarly, we find that option returns of MAX spread portfolios are not statistically significant regardless of the level of BV-SKEW. On the other hand, we observe that stock returns of MAX portfolios are negative but not highly significant for high ex-ante skewness OTM options. This finding shows that that OTM options do not exhibit lottery characteristics.

Deep-out-of-the-money Options. Table 3 presents results for DOTM options sorted on BV-SKEW and MAX. We find that option returns of MAX spread portfolios are always insignificant consistent with table 1 . However, the spread of the BV-SKEW portfolios is always negative and significant regardless of the state of the MAX. Furthermore, the payoffs are more pronounced when the MAX is low. Overall, this indicates that when the stocks do not have lottery characteristics, investors focus on the DOTM options. In other words, DOTM options replace stocks when these do not display lottery characteristics, a *substitution* effect. We also find that lottery stocks are not statistically significant for both BV-SKEW and MAX-sorted portfolios, indicating a preference for DOTM options as the "lottery of choice".

Overall, we find that there is some type of complementarity between ATM options and lottery stocks. On the other hand, we observe a substitution between lottery stock and option portfolios in DOTM options as lottery options yield high (in absolute value) negative returns when stocks do not have strong lottery characteristics.

[Table 3 about here.]

4.3 Cross-sectional Regressions

The previous section analyzes the performance of lottery stocks and lottery options in a non-parametric setting without restrictions that could be imposed in a functional model. However, this methodology does not allow us to control for different dimensions of lottery assets and also the aggregation imposed in the portfolios distorts part of the firm-level information. To this end, we run two pass regressions following Fama and MacBeth (1973) of option returns on the previous period MAX and BV-SKEW as well as 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), reversals (REV) and momentum (MOM)) that capture different dimension of the lottery strategies.[10] Specifically, we run a cross-sectional regression of the following form:

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

where $\text{RX}_{i,t+1}$ represents that option returns of asset i and $\mathbf{Z}_t$ represents the set of control variables. Table 4 reports average coefficients of the regression above as well as HAC t-statistics. We verify the increasing significance of MAX(10) (BV-SKEW) for ATM (DOTM) option returns. Specifically, we see that the negative relation between ATM options and MAX(10) remains statistically and economically significant after controlling for different determinants of lottery stocks. In addition, we find a positive relation between DOTM option returns and MAX(10) that is dominated by the presence of BV-SKEW in column (7) where the average coefficient of MAX(10) becomes insignificant as lottery investors have a higher preference for lottery options (e.g., substitution).

[Table 4 about here.]

[10] Appendix A provides a detailed description of the control variables.

5 Characteristics of Lottery Assets

In this section, we provide different explanations of the lottery choice between stocks and options. To this end, we consider signed and unsigned volume of the lottery strategies in the two markets in order to establish the direction of lottery demand. Later, we formally test the potential deviation from a no-arbitrage relation that it is related to the over/undervaluation of the options caused by investor demand as well as the role of short-selling constraints.

5.1 Unsigned Call Volume

We begin our analysis with the examination of the volume of call ratios within MAX and BV-SKEW portfolios so as to provide further evidence regarding the direction of lottery demand. Blau et al. (2014) show that call ratios (e.g., call option volume relative to call and put option volume) tend to increase with the lottery characteristics of the underlying asset. Similarly to our study, the authors focus on call options rather than put options as gamblers tend to exhibit higher preferences for call options due to their limited downside risk and the upside potential. While Blau et al. (2014) focus on the entire universe of options in order to compute the call ratios (on a quarterly basis), we evaluate the performance of call ratios across MAX(10) and BV-SKEW portfolios for different levels of moneyness (e.g., ATM, OTM and DOTM). To this end, we define call ratios as the volume of the call options of interest divided by the total volume of the call options written on the underlying asset.[11]

Table 5 shows time-series average of median call ratios of options allocated into double-sorted portfolios based on MAX(10) and BV-SKEW from 1996 to 2015. The call ratios take into consideration the holding period (e.g., 3 weeks until expiration) and the sorting

[11] We show results of call ratios that do not consider the volume of puts options because our main goal is examine whether the calls that we invest in exhibit higher volume relative to the universe of call options linked to a specific stock.

variables reflect information of the previous month. In order to reserve space we report results of the extreme portfolios as well as the corresponding spread portfolios.

Table 5 reports independent double sorts of spread call ratios based on the previous month MAX(10) or BV-SKEW. Thus, a negative spread portfolio indicates a negative relation between the call ratios and lottery characteristic of interest and vice versa. Particularly, we test whether the lotteryness in the stock market is more or less pronounced under different states of the lottery feature of the option market and vice versa. Starting with the ATM call options, we see the negative (positive) relation with respect to MAX(10) (BV-SKEW) tend to be higher for low BV-SKEW (low MAX(10)) portfolios. On the other hand, we see a reverse pattern in DOTM options where the positive (negative) pattern in MAX(10) (BV-SKEW) sorted portfolios is more extreme in low BV-SKEW (high MAX(10)) portfolios reinforcing the complementarity (ATM) and substitution effects (DOTM) documented in the previous section.

[Table 5 about here.]

5.2 Order Imbalances

One of the main drawbacks of using unsigned option volume is that we are not able to identify the direction of the trade. Thus, we construct a measure of directional trade (e.g., buy/sell transactions) which identifies the lottery choice in the two markets. In other words, a positive option (stock) order imbalance means that gamblers tend on average to buy lottery options (stocks) . Similarly, a negative option (stock) order imbalance shows that gamblers assign downward price pressure on lottery options (stocks).

In this section, we establish the informational role of transactions volume in lottery stocks and options by considering the order imbalances of the two strategies. If gamblers have an alternative lottery choice from which they can profit more, then their trading may have important implications not only for the prices of the lottery asset they invest in but also for the price of the alternative choice. In other words, the transactions of lottery options convey information not only for the prices of lottery options but also for the price of lottery stocks as the trading activity might be shifted from one asset to the other.

Here we ask whether the mispricing of ATM and DOTM options sorted on MAX is due to the trading activity between stocks and options with lottery characteristics. To this end, we report in Table 6 the order imbalances of stocks and options sorted on MAX or BV-SKEW from 2006 until 2013 based on the availability of the order imbalances from both the ISE and TAQ databases. The median portfolio-level order imbalances are aggregated from daily data and correspond to the life of the options (e.g., 3-week period since we buy the options the last trading day of the month). In other words, we compute the order imbalances during the holding period (e.g., we consider the trading activity of the option until expiration). *Panel A* shows results for options and *Panel B* shows results for stocks. We offer differences in imbalances between low(high) MAX or BV-SKEW portfolios under different levels of BV-SKEW or MAX. Thus, a negative value of the spread portfolio (HML) indicates a negative slope and vice versa.

Starting with ATM options, we find that the differences in the imbalances between low and high MAX portfolios are negative and statistically significant across BV-SKEW portfolios (e.g., negative slope). This finding indicates that gamblers are, on average, *net sellers* of ATM lottery options creating downward price pressure on such assets until their expiration. This is also an indication that ATM options become overvalued due to the lotteryness of the underlying asset. We also observe a similar pattern for lottery stocks with *high* BV-SKEW. In particular, gamblers are *net sellers* of lottery stocks with available lottery ATM options creating a feedback effect as the selling pressure in the options market is translated into a corresponding selling of lottery stocks. Thus, the MAX strategy becomes negative and statistically significant. On the other hand, we observe that gamblers tend to be *net buyers* of DOTM lottery options across different levels of MAX and *net sellers* of the corresponding stocks. In addition, there is no significant trading activity for lottery stocks indicating that gamblers substitute lottery stocks with lottery options when DOTM lottery options are available.

[Table 6 about here.]

Table 7 reports correlations of stock order imbalances of low and high MAX portfolios with option order imbalances of low and high BV-SKEW portfolios. We report *p*-values in parenthesis. In any case, we find that overtime gamblers tend to substitute lottery stocks with lottery options as the correlations of the imbalances of lottery stocks and options are negative (-0.31, -0.25 and -0.25 for ATM, OTM and DOTM options) and statistically significant. Figures 1 and 2 provide a visual representation of the stock and option imbalances. In figure 2 we decompose the option imbalances into small and large customers as well as firm-level imbalances and find that the substitution is more pronounced in the group of small customers. This is not surprising as institutional investors do not exhibit on average lottery preferences.

[Table 7 about here.]

[Figures 1 and 2 about here.]

5.3 Time-variation of Order Imbalances Around the Rebalancing Period

We investigate the behavior of stock and option order imbalances around the formation period. In particular, we consider a period of 10 days before and 15 days after the rebalancing date for the different moneyness intervals of interest. Figure 3 provides a visual illustration of daily stock (top panel) and option (bottom panel) order imbalances for ATM (Graph a), OTM (Graph b) and DOTM (Graph c) call options. The dashed line represents the cross-sectional average of the portfolios and the green (red) line display the low (high) MAX(10) or BV-SKEW portfolios. We find that for ATM options the difference in the order imbalances for both MAX(10) and BV-SKEW sorted portfolios are very close to zero. We also observe that gamblers are net sellers of lottery options on the rebalancing date and there is an increasing price pressure close to expiration. On the other hand, we see that gamblers are net buyers of lottery stocks and stocks with low BV-SKEW. In DOTM options we find that gamblers tend to be net buyers of low MAX and high BV-SKEW portfolios consistently with our previous findings. The corresponding order imbalances for stocks are more volatile (e.g., more overvalued low MAX and high BV-SKEW portfolios). Lottery seekers tend to be net buyers of high MAX and low BV-SKEW portfolios. The difference between extreme portfolios is more pronounced for BV-SKEW portfolios.

[Figures 3 about here.]

5.4 Disaggregated Option Order Imbalances

Here, we examine the variation of firm and customer order imbalances of options sorted based on MAX(10) and BV-SKEW. Figure A2 of the Internet Appendix shows the results for ATM, OTM and DOTM options. We find that for ATM options our results are mainly driven by small customers as they tend to be on average net sellers of ATM options sorted on MAX(10) or BV-SKEW and they become net buyers closer to expiration. On the other hand, firms tend to be net buyers of lottery options. For DOTM options we find that small customers are net buyers of low MAX and high BV-SKEW portfolios and firms are net buyers of low MAX and low BV-SKEW with decreasing price pressure closer to the expiration of the option.

5.5 Panel Regression Analysis

We investigate further the lottery demand between stocks and options. Specifically, we run panel regressions of order imbalances on the previous period MAX and BV-SKEW as well as a number of lagged control variables that capture different dimension of the lottery strategies. Our regressions that include month and firm fixed effects take the following form:

$$\text{OIMB}_{i,t+1} = \lambda_{0,t} + \lambda_{1,i}\text{MAX}(10)_{i,t} + \lambda_{2,i}\text{BV-SKEW}_{i,t} + \lambda'_{3,i}\mathbf{Z}_{i,t} + \varepsilon_{i,t+1} \quad (5)$$

$$\text{SIMB}_{i,t+1} = \phi_{0,t} + \phi_{1,i}\text{MAX}(10)_{i,t} + \phi_{2,i}\text{BV-SKEW}_{i,t} + \phi'_{3,i}\mathbf{Z}_{i,t} + \nu_{i,t+1} \quad (6)$$

where $\text{OIMB}_{i,t+1}$ ($\text{SIMB}_{i,t+1}$) denotes the option (stock) order imbalance 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).

Table 8 reports the coefficients from equation 5 (equation 6) of the lottery variables λ_1, λ_2 (ϕ_1, ϕ_2) and the control variables $\lambda_3^{'}$ ($\phi_3^{'}$) as well as the associated t-statistics. More precisely, we control for 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), reversals (REV) and momentum (MOM). We also report average adjusted R-squares. We find that the MAX is a key *negative* predictor of ATM, OTM and DOTM option and stock order imbalances. In addition, BV-SKEW is a *positive* (*negative*) predictor of option order imbalances of stock with ATM (DOTM) options and a *negative* (*positive*) predictor of stock order imbalances of stocks with ATM (OTM) options.

[Table 8 about here.]

5.6 Deviations from the Put-Call Parity Condition

In the previous section, we show that ATM options tend to be more *overvalued* as the MAX of the underlying asset increases and we illustrate that DOTM options are more *undervalued* with MAX. In this section, we formally test the potential deviation from a no-arbitrage relation that it is associated with the mispricing of the options induced by investor demand (e.g., Figlewski and Webb, 1993; Amin, Coval, and Seyhun, 2004). To this end, we examine whether the over (under)-valuation of the ATM (DOTM) call options correspond to violations of the put-call parity condition. In a world with no arbitrage opportunities, American options written on dividend paying stocks that exhibit identical strike prices and maturity dates should follow the boundary conditions below:

$$B_1 = C - P - S + PV(X) \leq 0, \tag{7}$$

$$B_2 = P - C + S - D - X \leq 0, \tag{8}$$

where S is the stock price, X represents the strike price, C (P) is the value of an American call (put) option and $PV(X)$ (D) is the present value of the strike price (the dividends paid during the life of the options). At the end of each month, we allocate options into quintiles based on the BV-SKEW or the MAX(10) of their underlying stock. Then we calculate the average level of mispricing per portfolio (e.g., B_1 and B_2) as well as the probability of a positive violation (e.g., Prob$[B_1 > 0]$ and Prob$[B_2 > 0]$) measured as the number of positive deviations divided by the total number of options in the portfolio. We also report the average value of the positive deviations (e.g., $E[B1|B1 > 0]$ and $E[B2|B2 > 0]$). Our analysis include all the available ATM call and put options, OTM call and *in-the-money* (ITM) put options or DOTM call and *deep-in-the-money* (DITM) put options according to the moneyness category of interest (e.g., ATM, OTM or DOTM). A violation of Eq. 7 implies that the call option is overvalued relative to the put option and the underlying stock and a violation of Eq. 8 indicates that the call option is undervalued relative to the put option and the stock or in other words the put and the stock are overvalued relatively to the call option.[12]

In this way, we ask whether the lottery characteristics of the options (BV-SKEW) or the underlying security (MAX(10)) lead to random or systematic violations of the aforementioned parity condition. The latter case would imply a violation of the no-arbitrage condition that it is associated with the mispricing of the option. Thus, *systematic* violations of the put-call parity condition should be associated with over (under)-valuation of the call options relatively to the underlying asset. For example, Byun and Kim (2016) focus on ATM options using quarterly data and find that the probability of a put-call parity violation increases with MAX, indicating a higher overvaluation of ATM options written on lottery stocks. This finding is also in line with Amin et al. (2004) who conclude that very positive market returns can cause deviations from the put-call parity condition as a result of an increase in the price of call options. This result remains robust after controlling for moneyness. In our setting, we test the existence of mispricing in lottery options as well as options attached to lottery equities and demonstrate that moneyness matters for lottery assets.

[12]Thus, a violation of the put-call parity condition implies for B_1 (B_2) that an investor can exploit the arbitrage opportunity by buying (shorting) the put option and the underlying security and selling (buying) the call option while borrowing (lending) the present value of the exercise price and the corresponding dividends.

Double Sorts. Table 9 shows deviations from the put-call parity condition for independent sorts portfolios on BV-SKEW and MAX. Specifically, we sort firm-level violations of the parity condition into quintile portfolios based on their previous period BV-SKEW and then within each portfolio we allocate the deviations based on MAX. *Panel A* of table 9 shows results for BV-SKEW portfolios. We see that ATM call options are undervalued for low MAX(10) portfolios. Consistently with table 3, we also find that DOTM call options are overvalued with an increasing probability of overvaluation when MAX(10) is high. *Panel B* of table 9 indicates that the spread portfolios of the violations of options sorted on MAX are positive (negative) for ATM and OTM (DOTM) options when BV-SKEW is low (high). This means that ATM and OTM (DOTM) options sorted on MAX tend to be more under (over)-valued when the lottery features of the options market are low (high).

[Table 9 about here.]

5.7 Short Interest and Lottery Demand

The previous section demonstrates that ATM (DOTM) call options tend to be more over (under)-valued as the lottery features of the underlying security become more pronounced. Ofek et al. (2004) find that short-sales constraints could be the reason why asymmetric violations of the put-call parity condition are driven by overvalued equities. To this end, we investigate in table 10 the magnitude of short interest in stocks sorted based on MAX(10) or BV-SKEW.

Bali et al. (2011) ask why the MAX effect they report is not traded away by other well-diversified investors. They claim that exploiting this phenomenon would require shorting stocks with extreme positive returns – which tend to be on average rather small and illiquid – which suggests that transaction costs may be an important impediment to engage in short-selling activities. Moreover, these small stocks tend to be held and traded by individual investors, rather than by institutions who might attempt to exploit this phenomenon.

Figlewski and Webb (1993) presents evidence that the use of option data corroborates information efficiency and the mitigation of transaction costs (e.g., Figlewski and Webb, 1993; Hu, 2014). In addition, Figlewski and Webb (1993) shows that option trading improves short-selling and helps negative information to have smaller impact on the underlying stock. Engelberg, Reed, and Ringgenberg (2014) also highlight the impact of stock short-selling on stock prices. Bris, Goetzmann, and Zhu (2007) find that markets with no short-selling constraints exhibit less negative skewness because news are faster incorporated into prices. In addition, lottery seekers obtain greater gain from investing in the options market rather than the stock market due to the fact that options offer higher financial leverage. For the same reason informed traders have a tendency to hold positions in the options market.

In line with Figlewski and Webb (1993), we find, in table 10, a significantly higher average level of short interest in the case of optionable stocks compared to stocks without options. One explanation of the insignificance of the MAX portfolio for stocks with options is that lottery stocks with options exhibit less pronounced spikes in their returns as investors with unfavourable information can sell short indirectly. As it is pointed out by Figlewski and Webb (1993), when a put is purchased from an options marker maker he will normally hedge by shorting the stock. Our conjecture is that the short interest and the shorting fees (table A3 of the Internet Appendix) should be higher for stocks with options. We see this pattern when we look at the positive and significant differences in short interest between low and high MAX stocks with options. This contradicts with the case of stocks without options where the level of short interest is very similar for low and high MAX stocks. In unreported results, we find that the level of short interest affects the returns of the stocks sorted on MAX as the strategy becomes very negative and significant when the level of short interest is low. It may be the case that the MAX is not traded away when it is more difficult to short the stock or find an appropriate indirectly short position.

Consistently with Ofek et al. (2004) we find that ATM call options sorted on MAX(10) are more overvalued and exhibit higher shorting interest. Thus, one explanation of the overvaluation of the ATM call options could be the excessive shorting interest. On the other hand, the shorting interest of high MAX(10) DOTM options is high but as we discussed in the previous sections the DOTM options are more undervalued as the MAX(10) increases. Thus the short interest cannot entirely explain the behavior of the DOTM option and it is rather the lottery investors demand that drive the undervaluation of the DOTM call options.

[Table 10 about here.]

6 Robustness

6.1 Order Imbalance of Lottery Stocks without Options

In this section, we explore the lottery demand for options without stocks. *Panel A* of Table 11 reports stock imbalances for the periods 1996-2013, 1996-2006 and 2006-2013. In all cases we find that investors are net sellers of high MAX portfolios (in contrast to stocks with options) meaning that they put negative price on the stock rendering a negative and statistically significant return. For this reason we observe that the MAX strategy is negative and statistically significant for stocks without options. We also report in *Panel B* and *Panel C* correlations of stocks without options sorted on MAX and BV-SKEW with optionable stocks as well as the corresponding option portfolios. Overall, we find that with options sorted on MAX or BV-SKEW exhibit low positive correlation with high MAX stocks without options. Interestingly, ATM options sorted on MAX(10) are not related to lottery stocks without options but the order imbalances of OTM and DOTM options of high MAX portfolios are negatively related with the corresponding portfolios of stocks without options. On the other hand, ATM and OTM call options of high BV-SKEW portfolios are negatively related to high MAX portfolios of stocks without options.[13]

[Table 11 about here.]

6.2 Conditional Lottery Stocks

Lottery Stocks with options. Here we ask whether the insignificance reported in table 1 for stocks *with* options alters once we control for different explanatory variables. To this end, we double sort stocks into quintiles based on the previous month 10-day maximum returns and a control variable. Specifically we investigate the performance of the MAX portfolios after considering momentum, reversals, illiquidity, size, book-to-market (B/M) ratio, idiosyncratic volatility, idiosyncratic skewness and institutional ownership.[14] *Panel A* of table 12 shows stocks returns of MAX portfolios that are averaged across the characteristic of interest. We find that MAX becomes negative and significant only when we control for momentum or size. This is not surprising as lottery returns are more pronounced across illiquid stocks with relatively small size. Indeed, we find negative and significant Fama and French (2014) alphas for MAX portfolios that control for illiquidity and book-to-market ratios.

Lottery Stocks without options. As mentioned in table 1, stocks without options that are sorted on the previous month 10-day maximum daily return (e.g., MAX(10)) exhibit negative and statistically significant spread portfolios. To this end, we investigate further the lotteryness of stocks *without* options. Particularly, in table 12 we allocate stocks into

[13] Figure A1 of the Internet Appendix provides a visual illustration of our findings.

[14] Appendix A offers a detailed description of the variables.

deciles based on their previous month daily maximum return and then within each MAX quintile portfolios conditional on the aforementioned characteristics. We find that the MAX strategy becomes insignificant in the case of reversals and institutional ownership. However, this result is not very strong as the corresponding Fama and French (2014) alphas are highly significant. This finding indicates, consistently with our hypothesis, that the MAX strategy is insignificant only for stocks with options as there is an upward price pressure in the stocks with options that does not allow the price to drop enough towards its fundamental value. Thus, the overvaluation of the lottery stocks with options is not as pronounced as in the case of stock without options.

[Table 12 about here.]

7 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. We also investigate the "lotteryness" of at-the-money, out-of-the-money or deep-out-of-the money options and find that lottery investors are willing to pay substantial premiums only for the lottery-like characteristics of DOTM.

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 there is a complementarity between ATM call options and stocks sorted on the previous month's maximum 10-day daily return (MAX) when the ex ante skewness of the options is *high*. On the other hand, there is a substitution between DOTM 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). Our results are reinforced by the direction and magnitude of stock and option order imbalances as well as the deviations of the put-call parity condition and the short interest.

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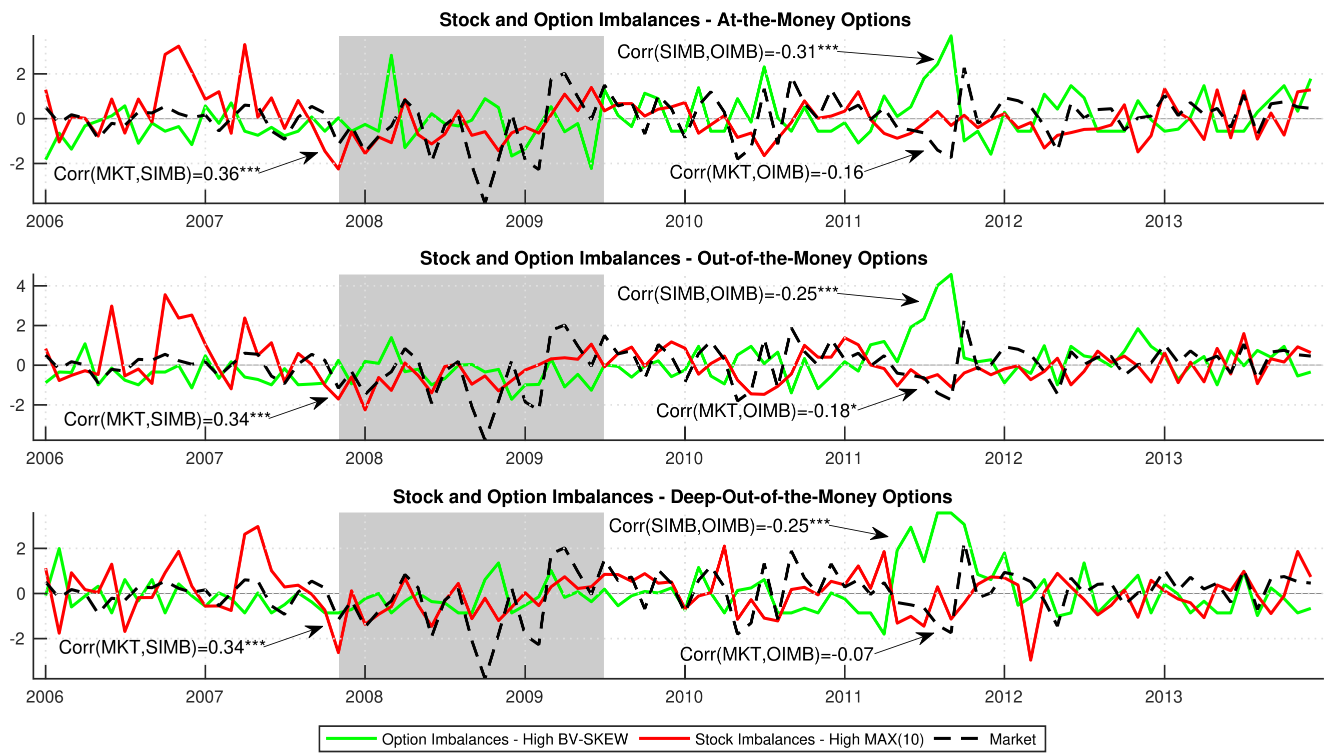
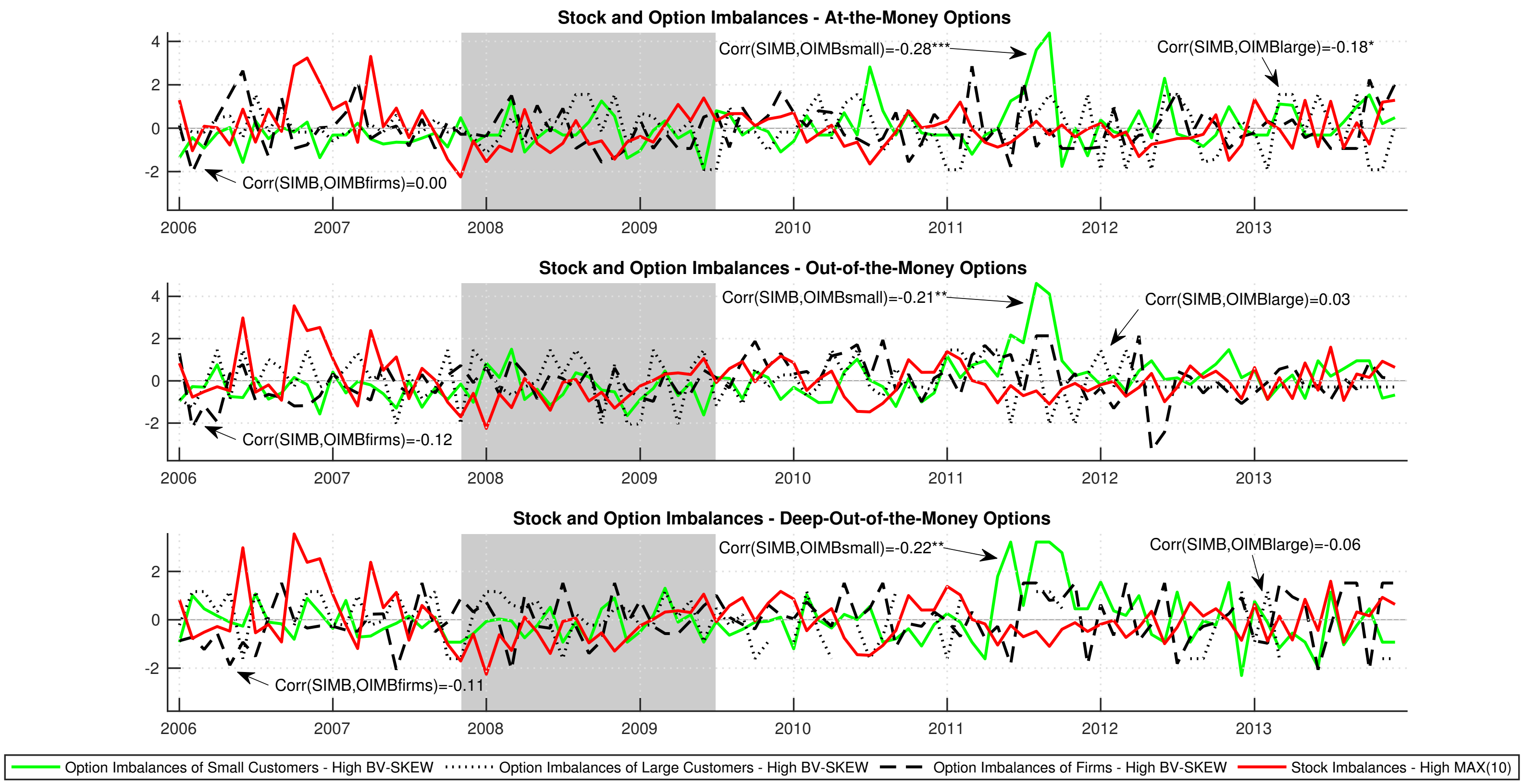
Figure 1. ***Order Imbalances of Lottery Stocks and Lottery Options***



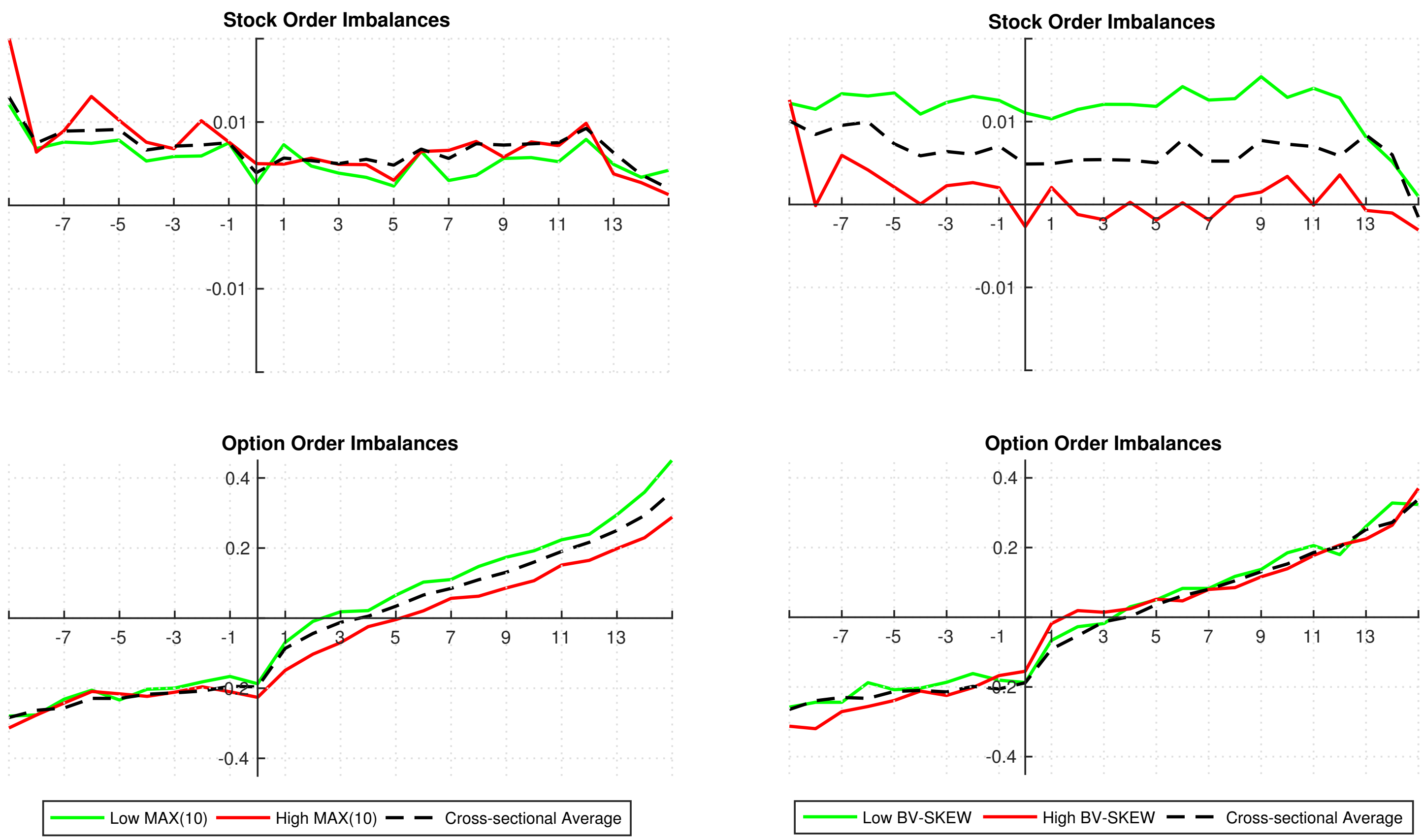
The figure displays order imbalances of lottery stocks (e.g., stock with the highest maximum daily return over the previous month) and lottery options (e.g., stock that exhibited the highest BV-SKEW over the previous month). We also report the excess return on the market. We also provide the correlations of the stock (SIMB) and option (OIMB) order imbalances as well as their comovement with the market excess return (MKT). The data is standardised and the results are based on the different levels of moneyness of the options. We denote with *, ** and *** the levels of significance at 10%, 5% and 1% respectively. The data are collected from TAQ and ISE and contain daily series (converted to monthly) from January 2006 to December 2013.

Figure 2. ***Customer and Firm Order Imbalances of Lottery Stocks and Lottery Options***



The figure displays customer-level (small or large) and firm-level order imbalances of lottery stocks (e.g., stock with the highest maximum daily return over the previous month) and lottery options (e.g., stock that exhibited the highest BV-SKEW over the previous month). We also provide the correlations of the stock (SIMB) and option (OIMB) order imbalances. The data is standardised and the results are based on the different levels of moneyness of the options. We denote with *, ** and *** the levels of significance at 10%, 5% and 1% respectively. The data are collected from TAQ and ISE and contain daily series (converted to monthly) from January 2006 to December 2013.

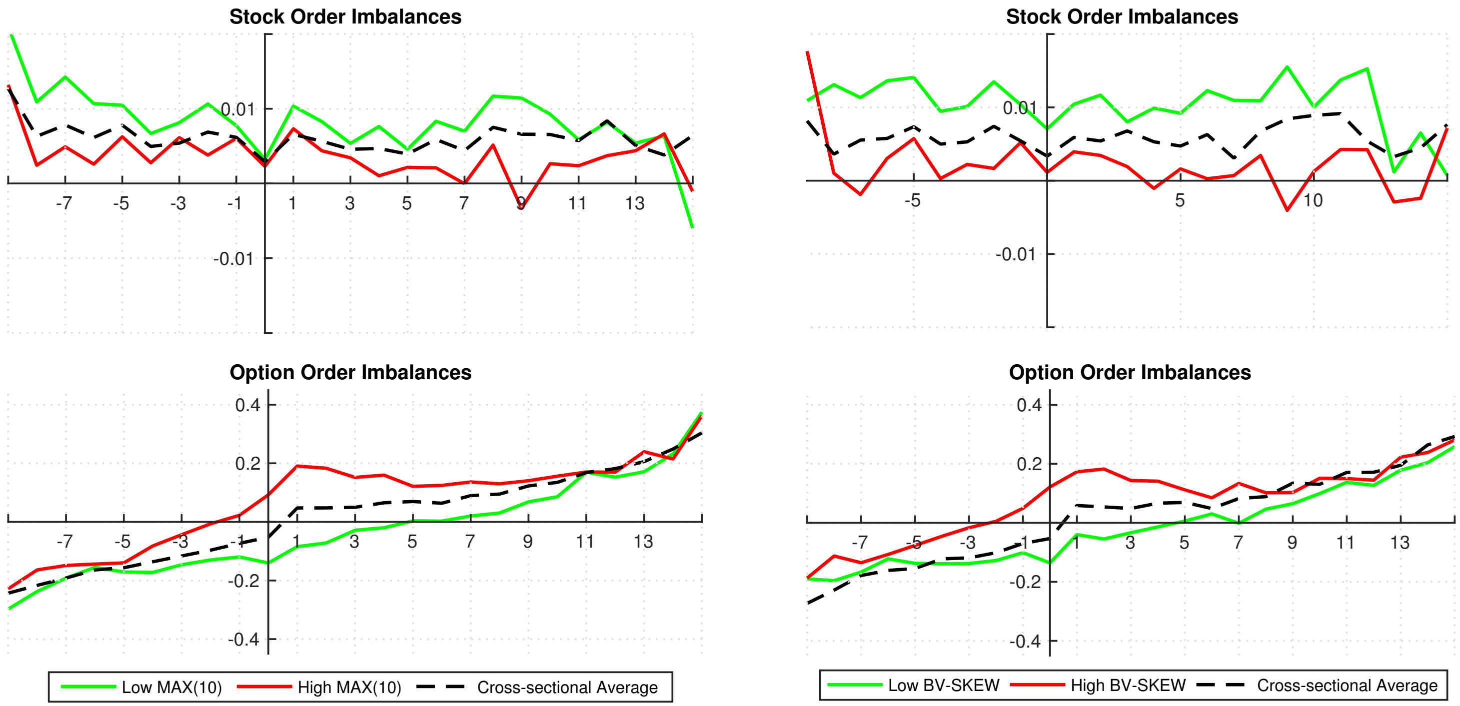
Figure 3. ***Order Imbalances Around the Formation Period***



(a) ***At-the-Money Options***

The figure displays order imbalances of stocks and options sorted on MAX(10) (e.g., stock with the highest maximum daily return over the previous month) and BV-SKEW. We report equal-weighted average order imbalance from nine trading days prior to the sorting date until 15 trading days after the sorting date. The cross-sectional average corresponds to the average order imbalance of all the assets or interest (e.g., across stocks or options) on each day. We offer results for at-the-money, out-of-the-money and deep-out-of-the-money options and their corresponding stocks. The data are collected from TAQ and ISE and contain daily series from January 2006 to December 2013.

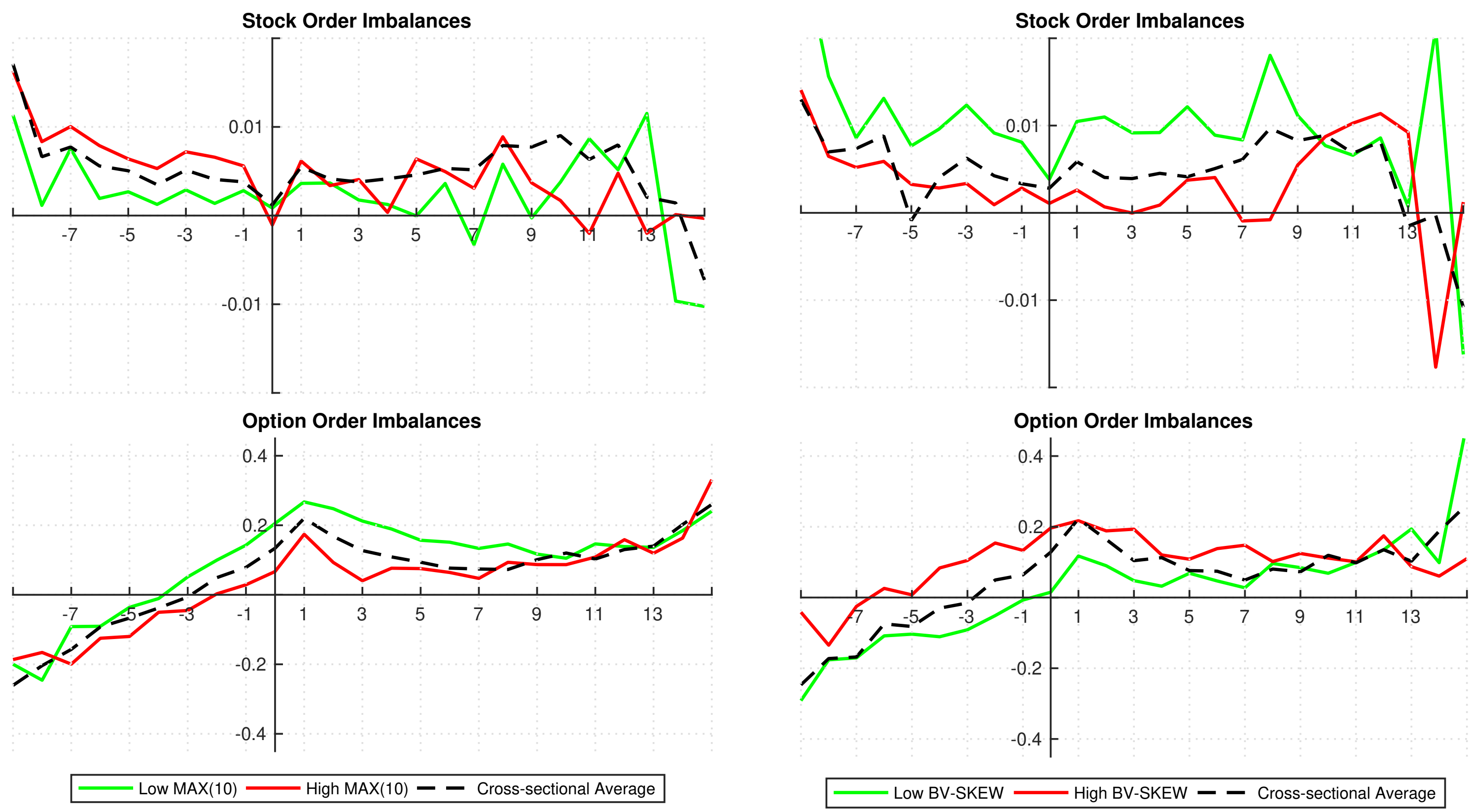
Figure 3. ***Order Imbalances Around the Formation Period*** *(continued)*



(b) ***Out-of-the-Money Options***

The figure displays order imbalances of stocks and options sorted on MAX(10) (e.g., stock with the highest maximum daily return over the previous month) and BV-SKEW. We report equal-weighted average order imbalance from nine trading days prior to the sorting date until 15 trading days after the sorting date. The cross-sectional average corresponds to the average order imbalance of all the assets or interest (e.g., across stocks or options) on each day. We offer results for at-the-money, out-of-the-money and deep-out-of-the-money options and their corresponding stocks. The data are collected from TAQ and ISE and contain daily series from January 2006 to December 2013.

Figure 3. ***Order Imbalances Around the Formation Period*** *(continued)*



(c) ***Deep-Out-of-the-Money Options***

The figure displays order imbalances of stocks and options sorted on MAX(10) (e.g., stock with the highest maximum daily return over the previous month) and BV-SKEW. We report equal-weighted average order imbalance from nine trading days prior to the sorting date until 15 trading days after the sorting date. The cross-sectional average corresponds to the average order imbalance of all the assets or interest (e.g., across stocks or options) on each day. We offer results for at-the-money, out-of-the-money and deep-out-of-the-money options and their corresponding stocks. The data are collected from TAQ and ISE and contain daily series from January 2006 to December 2013.

Table 1. Univariate Sorts based on MAX Returns

This table presents decile portfolios of stock returns sorted based on the MAX return for the period of July 1963 to January 1996 (*Panel A*) or for a sub-sample that starts from February 1996 (*Panel B*). *Panel C* reports average returns of MAX 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. *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 August 2015.

Panel A: 1963-1996

	MAX(5)				MAX(10)			
Decile	Avg Ret	t-stat	FF5 Alpha	t-stat	Avg Ret	t-stat	FF5 Alpha	t-stat
Low MAX	1.02	5.12	0.53	5.66	1.13	5.41	0.65	7.50
2	1.07	5.24	0.61	8.72	1.12	5.51	0.65	8.06
3	1.07	4.80	0.54	7.33	1.03	4.64	0.56	8.46
4	1.07	4.47	0.65	8.32	1.10	4.74	0.59	8.24
5	1.04	4.09	0.55	5.97	1.03	4.27	0.58	7.24
6	1.15	4.08	0.73	6.84	1.02	3.84	0.58	5.33
7	1.06	3.26	0.61	5.17	1.04	3.37	0.65	5.81
8	0.78	2.27	0.30	2.43	0.75	2.24	0.31	2.38
9	0.56	1.40	0.01	0.05	0.60	1.61	0.12	0.90
High MAX	-0.44	-1.04	-1.08	-5.81	-0.25	-0.59	-0.82	-4.26
HML	-1.46	-4.19	-1.61	-6.91	-1.38	-4.19	-1.47	-6.90

Panel B: 1996-2015

	MAX(5)				MAX(10)			
Decile	Avg Ret	t-stat	FF5 Alpha	t-stat	Avg Ret	t-stat	FF5 Alpha	t-stat
Low MAX	0.95	4.02	0.43	4.66	1.08	4.21	0.52	4.03
2	0.92	3.54	0.25	2.86	1.00	3.91	0.31	3.97
3	0.86	2.88	0.13	1.22	0.82	2.93	0.15	1.96
4	0.75	2.30	0.02	0.16	0.77	2.39	0.01	0.15
5	0.76	1.97	0.06	0.43	0.69	1.84	-0.04	-0.29
6	0.68	1.51	0.07	0.47	0.52	1.16	-0.12	-0.66
7	0.84	1.37	0.32	1.51	0.71	1.43	0.17	1.06
8	0.31	0.56	-0.17	-0.90	0.53	0.84	0.08	0.32
9	0.15	0.20	-0.22	-1.00	0.29	0.39	-0.05	-0.21
High MAX	0.32	0.35	0.10	0.22	0.13	0.15	-0.10	-0.24
HML	-0.63	-0.73	-0.33	-0.64	-0.94	-1.22	-0.62	-1.41

Panel C: 1996-2015 (Conditional on Options)

	MAX(5)				MAX(10)			
Decile	Avg Ret With Options	t-stat	Avg Ret No Options	t-stat	Avg Ret With Options	t-stat	Avg Ret No Options	t-stat
Low MAX	0.61	2.51	0.97	4.00	0.82	3.10	1.15	4.67
2	0.75	2.85	0.93	3.45	0.81	3.11	1.03	3.89
3	0.71	2.39	0.86	2.55	0.71	2.48	0.65	1.89
4	0.55	1.67	0.64	1.61	0.48	1.46	0.73	1.99
5	0.50	1.38	0.82	2.22	0.49	1.44	0.79	2.31
6	0.50	1.18	0.49	1.01	0.35	0.87	0.50	1.05
7	0.58	1.20	0.62	1.09	0.49	0.94	0.63	1.17
8	0.40	0.68	0.31	0.42	0.52	0.99	0.17	0.24
9	0.28	0.42	-0.02	-0.02	0.32	0.49	0.29	0.35
High MAX	0.14	0.19	-0.60	-0.64	0.13	0.17	-0.80	-0.88
HML	-0.47	-0.72	-1.57	-1.81	-0.69	-1.06	-1.95	-2.42
FF5 Alpha	-0.24	-0.79	-1.12	-2.79	-0.44	-1.34	-1.50	-3.90

Table 2. Univariate Sorts based on BV-SKEW

This table presents decile portfolios of options returns sorted based on BV-SKEW for different intervals of moneyness. We also report the corresponding alphas of the Five-factor Fama and French (2014) model. Excess 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 August 2015.

Option Returns												
Lottery Features	Low	2	3	4	5	6	7	8	9	High	HML	FF5 Alpha
						At-the-money Options						
BV-SKEW	0.02	0.05	0.05	0.05	0.07	0.06	0.04	0.01	0.08	0.08	0.06	0.01
	[0.63]	[1.36]	[1.37]	[1.25]	[1.64]	[1.28]	[0.96]	[0.31]	[1.54]	[1.49]	[1.63]	[0.27]
						Out-of-the-money Options						
BV-SKEW	-0.01	-0.05	-0.01	0.02	0.04	0.07	-0.02	0.02	0.02	0.03	0.04	0.04
	[-0.14]	[-0.79]	[-0.12]	[0.28]	[0.59]	[1.09]	[-0.24]	[0.26]	[0.31]	[0.42]	[0.45]	[0.45]
						Deep-out-of-the-money Options						
BV-SKEW	-0.04	-0.10	-0.01	-0.15	-0.12	-0.22	-0.25	-0.23	-0.42	-0.66	-0.63	-0.62
	[-0.41]	[-0.98]	[-0.07]	[-1.90]	[-1.58]	[-3.15]	[-3.20]	[-2.44]	[-6.21]	[-17.33]	[-6.34]	[-6.12]

Table 3. Double Sorts - 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). P-values are in parenthesis. The data is collected from CRSP and OptionMetrics IvyDB database contain monthly series from January 1996 to August 2015.

Panel A: Option Returns

	At-the-money Options			*Out-of-the-money Options*			*Deep-out-of-the-money Options*		
	Low MAX	2	High MAX	Low MAX	2	High MAX	Low MAX	2	High MAX
$HML^{BV-SKEW}$	0.06	0.00	-0.03	0.00	-0.03	0.05	-0.42	-0.31	-0.25
	[1.91]	[0.17]	[-1.01]	[0.02]	[-0.41]	[0.53]	[-3.74]	[-3.69]	[-1.78]
	Low BV-SKEW	2	High BV-SKEW	Low BV-SKEW	2	High BV-SKEW	Low BV-SKEW	2	High BV-SKEW
$HML^{MAX(10)}$	-0.07	-0.13	-0.16	-0.08	-0.04	-0.04	-0.04	-0.13	0.13
	[-1.87]	[-3.71]	[-4.34]	[-1.20]	[-0.57]	[-0.53]	[-0.26]	[-1.34]	[0.97]

Panel B: Stock Returns

	At-the-money Options			*Out-of-the-money Options*			*Deep-out-of-the-money Options*		
	Low MAX	2	High MAX	Low MAX	2	High MAX	Low MAX	2	High MAX
$HML^{BV-SKEW}$	0.29	0.04	-0.88	-0.39	-0.72	-0.78	0.20	-0.83	-0.59
	[1.61]	[0.16]	[-2.04]	[-1.17]	[-2.05]	[-1.36]	[0.55]	[-2.51]	[-1.48]
	Low BV-SKEW	2	High BV-SKEW	Low BV-SKEW	2	High BV-SKEW	Low BV-SKEW	2	High BV-SKEW
$HML^{MAX(10)}$	-0.11	-0.57	-1.28	-0.61	-0.43	-1.09	0.03	-0.79	-0.76
	[-0.26]	[-1.41]	[-2.18]	[-1.31]	[-0.98]	[-1.66]	[0.07]	[-1.49]	[-1.26]

Table 4. Cross-Sectional Regressions - Option Returns

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), reversals (REV) and momentum (MOM). The model takes the following form:

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

where $\text{RX}_{i,t+1}$ denotes the 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 is 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 August 2015.

Option Returns									
	At-the-money Options			*Out-of-the-money Options*			*Deep-out-of-the-money Options*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.124	0.034	-0.141	0.029	-0.043	0.007	-0.390	-0.231	0.850
t-stats	[2.45]	[0.91]	[-1.22]	[0.44]	[-0.64]	[0.03]	[-6.54]	[-4.14]	[3.69]
$\text{MAX(10)}_{i,t}$	-4.647		-4.947	-2.562		-4.889	4.312		-5.396
t-stats	[-4.18]		[-3.08]	[-1.44]		[-1.33]	[1.83]		[-1.48]
$\text{BV-SKEW}_{i,t}$		0.005	-0.003		0.010	-0.002		-0.003	-0.003
t-stats		[0.56]	[-0.35]		[0.94]	[-0.19]		[-2.97]	[-3.24]
$\text{Ln(Size)}_{i,t}$			0.025			0.005			-0.069
t-stats			[3.10]			[0.32]			[-4.42]
$\text{Ln(Price)}_{i,t}$			-0.038			-0.039			0.016
t-stats			[-2.55]			[-1.16]			[0.29]
$\text{IOR}_{i,t}$			-0.005			0.048			-0.145
t-stats			[-0.18]			[0.67]			[-1.18]
$\text{B/M}_{i,t}$			0.032			0.107			0.121
t-stats			[1.93]			[2.40]			[1.97]
$\text{D/A}_{i,t}$			-0.009			-0.093			-0.127
t-stats			[-0.26]			[-1.29]			[-1.18]
$\text{Turnover}_{i,t}$			0.009			0.008			0.007
t-stats			[2.75]			[0.88]			[0.73]
$\text{IVOL}_{i,t}$			-0.401			0.074			-1.456
t-stats			[-0.35]			[0.02]			[-0.54]
$\text{REV}_{i,t}$			-0.002			-0.293			0.412
t-stats			[-0.01]			[-1.29]			[1.73]
$\text{MOM}_{i,t}$			0.027			0.027			0.102
t-stats			[0.93]			[0.49]			[1.95]
Adj-R^2	1.05%	0.86%	5.66%	0.78%	0.73%	6.20%	0.51%	0.19%	5.41%

Table 5. Call Volume Ratios

This table presents the time-series average of the median option call ratios of option portfolios double-sorted on 10-day maximum daily stock returns (e.g., MAX(10)) or the Boyer and Vorkink (2014) measure of ex ante skewness of call options (e.g., BV-SKEW) respectively. We define the call ratios as the volume of the call options of interest divided by the total volume of all the options written on the underlying stock. We report results for different moneyness categories. 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 datasets and contain monthly series from January 1996 to August 2015.

	Call ratios								
Lottery Features	Low	High	HML	Low	High	HML	Low	High	HML
	At-the-money Options			*Out-of-the-money Options*			*Deep-out-of-the-money Options*		
	Low MAX	2	High MAX	Low MAX	2	High MAX	Low MAX	2	High MAX
$HML^{BV-SKEW}$	22.49	18.56	14.73	-10.92	-4.91	4.45	-6.18	-2.81	-4.19
	[12.51]	[11.04]	[12.34]	[-5.54]	[-3.31]	[2.77]	[-6.94]	[-6.26]	[-7.11]
	Low BV-SKEW	2	High BV-SKEW	Low BV-SKEW	2	High BV-SKEW	Low BV-SKEW	2	High BV-SKEW
$HML^{MAX(10)}$	-0.89	-7.01	-8.66	-1.65	5.93	13.51	-1.74	-1.57	0.25
	[-0.82]	[-5.04]	[-6.06]	[-1.03]	[3.86]	[6.42]	[-2.28]	[-3.96]	[0.94]

Table 6. Order Imbalances of Lottery Stocks and Options

This table presents the time-series average of the median stock and option imbalances (expressed in percentage points) of portfolios of stock and options sorted on 10-day maximum daily stock returns (e.g., MAX(10)) or 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) order imbalances. The order imbalances take into consideration the period of rebalancing until the expiration of the options (e.g., three weeks). 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). P-values are in parenthesis. The data is collected from CRSP, OptionMetrics IvyDB, TAQ as well as ISE datasets and contain monthly series from January 2006 to December 2013.

Panel A: Option Order Imbalances

	At-the-money Options			*Out-of-the-money Options*			*Deep-out-of-the-money Options*		
	Low MAX	2	High MAX	Low MAX	2	High MAX	Low MAX	2	High MAX
$HML^{BV-SKEW}$	-0.02	0.00	0.00	-0.12	-0.10	-0.12	0.06	0.05	0.10
	[-1.72]	[0.32]	[0.56]	[-6.26]	[-9.99]	[-4.08]	[2.76]	[1.95]	[2.96]
	Low BV-SKEW	2	High BV-SKEW	Low BV-SKEW	2	High BV-SKEW	Low BV-SKEW	2	High BV-SKEW
$HML^{MAX(10)}$	-0.09	-0.06	-0.07	0.04	0.02	0.03	-0.13	-0.06	-0.08
	[-6.55]	[-7.10]	[-6.94]	[1.73]	[1.37]	[1.31]	[-4.90]	[-2.06]	[-3.62]

Panel B: Stock Order Imbalances

	At-the-money Options			*Out-of-the-money Options*			*Deep-out-of-the-money Options*		
	Low MAX	2	High MAX	Low MAX	2	High MAX	Low MAX	2	High MAX
$HML^{BV-SKEW}$	-0.00	-0.00	-0.01	0.00	0.00	-0.01	-0.01	0.00	-0.01
	[-3.02]	[-3.65]	[-5.78]	[-1.75]	[-2.47]	[-4.68]	[-2.30]	[-1.31]	[-2.62]
	Low BV-SKEW	2	High BV-SKEW	Low BV-SKEW	2	High BV-SKEW	Low BV-SKEW	2	High BV-SKEW
$HML^{MAX(10)}$	0.00	0.00	-0.00	0.00	-0.00	-0.00	0.00	-0.00	0.00
	[1.78]	[0.40]	[-1.79]	[0.06]	[-1.23]	[-2.21]	[0.69]	[-0.66]	[0.77]

Table 7. Correlations of Order Imbalances of Lottery Stocks and Options

This table presents correlations (expressed in percentage points) of the median stock and option imbalances of portfolios of stock and options sorted on 10-day maximum daily stock returns (e.g., MAX(10)) or the Boyer and Vorkink (2014) measure of ex ante skewness of call options (e.g., BV-SKEW) respectively. *Panel A* shows correlations of the order imbalances (OIMB) of lottery stocks and lottery options while *Panel B* displays correlations of order imbalances of stocks that have lottery options and options of stocks with lottery characteristics. The order imbalances take into consideration the period of rebalancing until the expiration of the options (e.g., three weeks). 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). P-values are in parenthesis. The data is collected from CRSP, OptionMetrics IvyDB, TAQ as well as ISE datasets and contain monthly series from January 2006 to December 2013.

Panel A: Correlations of IMBs of lottery stocks with lottery options						
Lottery Features	Low	High	Low	High	Low	High
	At-the-money Options		*Out-of-the-money Options*		*Deep-out-of-the-money Options*	
corr($SIMB^{MAX(10)}$, $OIMB^{BV-SKEW}$)	0.07	-0.31	-0.19	-0.25	-0.09	-0.25
	[0.48]	[0.00]	[0.07]	[0.01]	[0.40]	[0.01]
Panel B: Correlations of IMBs of stocks linked to lottery options and options of lottery stocks						
Lottery Features	Low	High	Low	High	Low	High
	At-the-money Options		*Out-of-the-money Options*		*Deep-out-of-the-money Options*	
corr($OIMB^{MAX(10)}$, $Stock^{BV-SKEW}$)	-0.12	-0.17	-0.11	-0.16	-0.31	-0.18
	[0.24]	[0.09]	[0.30]	[0.13]	[0.00]	[0.09]

Table 8. Panel Regression Analysis of Order Imbalances

This table presents panel regressions of option and stock order imbalances 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), reversals (REV) and momentum (MOM). The model takes the following form:

$$\text{OIMB}_{i,t+1} = \lambda_{0,t} + \lambda_{1,i}\text{MAX(10)}_{i,t} + \lambda_{2,i}\text{BV-SKEW}_{i,t} + \lambda'_{3,i}\mathbf{Z}_{i,t} + \varepsilon_{i,t+1}$$

$$\text{SIMB}_{i,t+1} = \phi_{0,t} + \phi_{1,i}\text{MAX(10)}_{i,t} + \phi_{2,i}\text{BV-SKEW}_{i,t} + \phi'_{3,i}\mathbf{Z}_{i,t} + \nu_{i,t+1}$$

where $\text{OIMB}_{i,t+1}$ ($\text{SIMB}_{i,t+1}$) denotes the option (stock) order imbalance 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 consider both month and firm fixed effects and report t-statistics is squared brackets. The table also shows average of the adjusted R^2 obtained from the time-series regressions. The data is collected from CRSP, OptionMetrics IvyDB, TAQ as well as ISE datasets and contain monthly series from January 2006 to December 2013.

Order Imbalances						
	At-the-money Options		*Out-of-the-money Options*		*Deep-out-of-the-money Options*	
	$\text{OIMB}_{i,t+1}$	$\text{SIMB}_{i,t+1}$	$\text{OIMB}_{i,t+1}$	$\text{SIMB}_{i,t+1}$	$\text{OIMB}_{i,t+1}$	$\text{SIMB}_{i,t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-0.029	0.045	-0.202	0.037	-0.360	0.039
t-$stats$	[-0.19]	[2.44]	[-0.84]	[1.41]	[-1.24]	[1.27]
$\text{MAX(10)}_{i,t}$	-2.028	-0.097	-4.066	-0.135	-1.280	-0.122
t-$stats$	[-5.74]	[-2.33]	[-6.87]	[-2.07]	[-2.18]	[-1.99]
$\text{BV-SKEW}_{i,t}$	0.009	-0.001	0.000	0.000	0.000	0.000
t-$stats$	[6.10]	[-4.66]	[1.31]	[2.22]	[-2.18]	[-1.16]
$\text{Ln(Size)}_{i,t}$	0.003	-0.002	0.026	0.000	0.029	-0.001
t-$stats$	[0.25]	[-1.17]	[1.44]	[-0.23]	[1.26]	[-0.23]
$\text{Ln(Price)}_{i,t}$	-0.008	0.003	-0.014	0.002	0.000	0.002
t-$stats$	[-0.61]	[2.07]	[-0.76]	[0.76]	[0.01]	[0.97]
$\text{IOR}_{i,t}$	0.007	-0.001	-0.052	-0.001	0.055	-0.013
t-$stats$	[0.45]	[-0.80]	[-1.37]	[-0.30]	[1.24]	[-2.69]
$\text{B/M}_{i,t}$	0.016	0.002	0.001	0.002	-0.011	0.000
t-$stats$	[2.25]	[2.53]	[0.07]	[1.26]	[-0.93]	[0.35]
$\text{D/A}_{i,t}$	-0.033	0.014	0.041	0.009	-0.010	0.012
t-$stats$	[-1.17]	[4.25]	[0.94]	[1.80]	[-0.19]	[2.22]
$\text{Turnover}_{i,t}$	-0.005	-0.001	-0.002	-0.001	0.001	0.000
t-$stats$	[-4.38]	[-5.20]	[-0.98]	[-3.42]	[0.44]	[-1.65]
$\text{IVOL}_{i,t}$	-0.770	-0.093	-0.017	-0.032	-0.305	-0.043
t-$stats$	[-2.93]	[-3.00]	[-0.04]	[-0.70]	[-0.70]	[-0.93]
$\text{REV}_{i,t}$	0.141	0.020	-0.004	0.027	-0.149	0.018
t-$stats$	[6.32]	[7.58]	[-0.10]	[6.26]	[-3.74]	[4.20]
$\text{MOM}_{i,t}$	0.000	0.004	-0.024	0.005	-0.007	0.002
t-$stats$	[-0.03]	[6.23]	[-2.55]	[5.04]	[-0.74]	[2.16]
Adj-R^2	3.67%	9.76%	6.48%	11.20%	5.38%	9.66%
Stock Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Table 9. Put-Call Parity Violations

This table presents tests of put-call parity violations. We focus on 1-month options within different moneyness (X/S) bins (e.g., options with moneyness close to 1, 1.10 or greater than 1.10) To this end, positive values of B_1 and B_2 as associated with deviations from the put-call parity conditions and thus indicate over/under-valuation of the options of interest. Thus, B_1 and B_2 are estimated as

$$B_1 = C - P - S + PV(X),$$

$$B_2 = P - C + S - D - X,$$

where S is the stock price, X represents the strike price, C (P) is the value of an American call (put) option and $PV(X)$ (D) is the present value of the strike price (the dividends paid during the life of the options). At the end of each month, we allocate options into quintiles based on the MAX(10) return of their underlying stocks. Then we calculate the average level of mispricing per portfolio (e.g., B_1 and B_2) as well as the probability of a positive violation (e.g., Prob[$B_1 > 0$] and Prob[$B_2 > 0$]) measured as the number of positive deviations divided by the total number of options in the portfolio. We also report the average value of the positive deviations (e.g., E[$B1|B1 > 0$] and E[$B2|B2 > 0$]). *Panel A* shows option violation of spread portfolios of options sorted on MAX(10) and BV-SKEW and *Panel* show the corresponding results when sorting first on BV-SKEW and then within the BV-SKEW portfolios we sort based on MAX(10). We also display Newey and West (1987) t-statistics is squared brackets corrected for autocorrelation and heteroskedasticity. The data is collected from CRSP and contain monthly series from January 1996 to August 2015.

Panel A: Options Sorted on MAX(10) and BV-SKEW

$Spread\ portfolios$	Low MAX	2	High MAX	Low MAX	2	High MAX	Low MAX	2	High MAX
	At-the-money Options			*Out-of-the-money Options*			*Deep-out-of-the-money Options*		
$HML^{BV-SKEW}_{E[B_1]}$	-0.01	-0.01	-0.03	0.00	-0.01	-0.01	0.10	0.09	0.03
	[-2.90]	[-3.47]	[-4.83]	[0.79]	[-1.27]	[-1.92]	[3.63]	[3.06]	[6.43]
$HML^{BV-SKEW}_{Prob[B_1>0]]}$	-0.04	-0.05	-0.09	0.01	-0.02	-0.03	0.13	0.12	0.10
	[-4.65]	[-4.88]	[-8.48]	[1.24]	[-0.13]	[-2.72]	[14.14]	[12.95]	[11.38]
$HML^{BV-SKEW}_{E[B1\|B1>0]]}$	-0.00	-0.01	-0.02	0.01	0.00	-0.01	0.08	0.08	0.02
	[-1.71]	[-3.83]	[-7.16]	[3.13]	[1.87]	[-1.94]	[3.21]	[2.65]	[7.65]
$HML^{BV-SKEW}_{E[B_2]]}$	0.11	0.10	0.08	0.16	0.13	0.07	0.14	0.15	0.20
	[4.82]	[5.31]	[4.82]	[16.62]	[12.75]	[6.42]	[6.17]	[5.52]	[12.46]
$HML^{BV-SKEW}_{Prob[B_2>0]]}$	0.09	0.11	0.14	0.21	0.19	0.13	0.28	0.28	0.24
	[13.17]	[13.08]	[13.16]	[17.42]	[14.36]	[10.04]	[24.31]	[19.37]	[14.94]
$HML^{BV-SKEW}_{E[B2\|B2>0]]}$	0.01	0.02	0.02	0.13	0.11	0.06	0.17	0.18	0.16
	[9.72]	[8.45]	[6.25]	[18.75]	[14.50]	[6.60]	[20.24]	[16.05]	[12.10]

Panel B: Options Sorted on BV-SKEW and MAX(10)

$Spread\ portfolios$	Low BV-SKEW	2	High BV-SKEW	Low BV-SKEW	2	High BV-SKEW	Low BV-SKEW	2	High BV-SKEW
	At-the-money Options			*Out-of-the-money Options*			*Deep-out-of-the-money Options*		
$HML^{MAX}_{E[B_1]}$	0.02	0.01	0.00	0.02	0.00	0.00	-0.01	0.00	-0.07
	[6.24]	[1.61]	[0.49]	[4.14]	[0.60]	[0.31]	[-1.07]	[0.66]	[-2.73]
$HML^{MAX}_{Prob[B_1>0]]}$	0.04	0.01	-0.01	0.04	0.01	-0.01	0.03	0.02	-0.01
	[4.81]	[2.01]	[-0.94]	[3.53]	[1.52]	[-0.66]	[2.67]	[1.68]	[-0.86]
$HML^{MAX}_{E[B1\|B1>0]]}$	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	-0.06
	[6.40]	[0.81]	[-0.80]	[5.81]	[0.48]	[0.12]	[-0.36]	[1.30]	[-2.53]
$HML^{MAX}_{E[B_2]]}$	0.05	0.07	0.03	0.01	0.01	-0.07	0.04	0.09	0.10
	[4.77]	[2.16]	[3.33]	[2.29]	[0.31]	[-6.12]	[5.51]	[5.43]	[3.23]
$HML^{MAX}_{Prob[B_2>0]]}$	0.06	0.09	0.11	0.06	0.10	-0.02	0.07	0.09	0.03
	[7.48]	[11.17]	[11.15]	[7.27]	[8.42]	[-1.57]	[7.59]	[10.71]	[3.51]
$HML^{MAX}_{E[B2\|B2>0]]}$	0.01	0.02	0.02	0.02	0.05	-0.05	0.04	0.08	0.03
	[5.94]	[6.81]	[6.80]	[6.45]	[5.17]	[-5.63]	[6.20]	[4.99]	[2.38]

Table 10. Lottery Assets and Short Interest

This table presents the median average of the short interest of stocks sorted based on MAX(10) and BV-SKEW. *Panel A* shows results based on single sorts of stocks with and without options on MAX(10) and BV-SKEW and *Panel* presents the corresponding results of dependent and independent double-sorts on MAX(10) and BV-SKEW and *vice versa* (*Panel C*). We also display Newey and West (1987) t-statistics is squared brackets corrected for autocorrelation and heteroskedasticity. The data is collected from CRSP and OptionMetrics IvyDB database and contain monthly series from January 1996 to August 2015.

Panel A: Univariate Sorts

Spread portfolios	Low MAX	High MAX	HML	Low BV-SKEW	High BV-SKEW	HML
			Stocks with at-the-money options			
Short Interest	2.06	6.09	4.02	2.91	3.76	0.85
	[17.49]	[13.52]	[11.44]	[12.23]	[11.88]	[6.28]
			Stocks with out-of-the-money options			
Short Interest	2.02	6.48	4.45	5.31	2.01	-3.31
	[19.40]	[13.35]	[11.14]	[13.17]	[17.93]	[-10.37]
			Stocks with deep-out-of-the-money options			
Short Interest	3.18	7.80	4.62	6.06	4.01	-2.05
	[12.90]	[14.24]	[12.21]	[14.19]	[11.81]	[-7.96]
		Stocks without options				
Short Interest	0.53	0.47	-0.06			
	[7.00]	[10.19]	[-0.90]			

Panel B: Double sorts on BV-SKEW and MAX(10)

Spread portfolios	Low MAX	2	High MAX
		Stocks with at-the-money options	
$HML^{BV-SKEW}_{Short\ Interest}$	0.00	0.01	0.01
	[5.65]	[5.51]	[6.39]
		Stocks with out-of-the-money options	
$HML^{BV-SKEW}_{Short\ Interest}$	-0.01	-0.01	0.00
	[-7.56]	[-6.51]	[0.95]
		Stocks with deep-out-of-the-money options	
$HML^{BV-SKEW}_{Short\ Interest}$	-0.02	0.00	0.01
	[-7.11]	[-0.94]	[5.41]

Panel C: Double sorts on MAX(10) and BV-SKEW

Spread portfolios	Low BV-SKEW	2	High BV-SKEW
		Stocks with at-the-money options	
$HML^{MAX}_{Short\ Interest}$	0.02	0.03	0.03
	[10.21]	[10.91]	[10.85]
		Stocks with out-of-the-money options	
$HML^{MAX}_{Short\ Interest}$	0.02	0.02	0.03
	[10.22]	[9.65]	[10.63]
		Stocks with deep-out-of-the-money options	
$HML^{MAX}_{Short\ Interest}$	0.02	0.03	0.05
	[5.94]	[9.68]	[10.76]

Table 11. Order Imbalances of Lottery Stocks without Options

This table presents time-series averages of the median stock imbalances (expressed in percentage points) of portfolios of no option stocks sorted on 10-day maximum daily stock returns (e.g., MAX(10)). *Panel A* shows stock order imbalances. *Panel B* shows correlations of the order imbalances (OIB) of lottery stocks and lottery options while *Panel C* displays correlations of order imbalances of stocks that have lottery options and options of stocks with lottery characteristics. 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). P-values are in parenthesis. The data is collected from CRSP, OptionMetrics IvyDB, TAQ as well as ISE datasets and contain monthly series from February 1996 to December 2013.

Panel A: Stock Order Imbalance

Lottery Features	Low	High	HML	Low	High	HML	Low	High	HML
	1996-2013			*1996-2006*			*2006-2013*		
MAX(10)	-1.56	-4.09	-2.54	-0.03	-0.06	-0.04	-0.16	-1.27	-1.11
	[-2.40]	[-5.31]	[-4.10]	[-2.86]	[-7.09]	[-4.34]	[-0.64]	[-2.28]	[-2.20]

Panel B: Correlations of IMBs of stocks and options sorted on MAX with no option lottery stocks

Lottery Features	Low	High	Low	High	Low	High
	At-the-money Options		*Out-of-the-money Options*		*Deep-out-of-the-money Options*	
corr($SIMB^{MAX(10)}$, $SIMB^{MAX(10)}_{No\ Options}$)	0.38	0.50	0.39	0.36	0.24	0.31
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
corr($OIMB^{MAX(10)}$, $SIMB^{MAX(10)}_{No\ Options}$)	0.16	0.01	-0.11	-0.24	-0.29	-0.36
	(0.11)	(0.95)	(0.29)	(0.02)	(0.00)	(0.00)

Panel C: Correlations of IMBs of stocks and options sorted on BV-SKEW with no option lottery stocks

Lottery Features	Low	High	Low	High	Low	High
	At-the-money Options		*Out-of-the-money Options*		*Deep-out-of-the-money Options*	
corr($SIMB^{BV-SKEW}$, $SIMB^{MAX(10)}_{No\ options}$)	0.38	0.34	0.47	0.28	0.39	0.29
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
corr($OIMB^{BV-SKEW}$, $SIMB^{MAX(10)}_{No\ Options}$)	0.18	-0.30	-0.23	-0.29	-0.13	-0.16
	(0.07)	(0.00)	(0.02)	(0.00)	(0.20)	(0.11)

Table 12. Conditional Lottery Stocks with and without Options

This table presents portfolios of stocks with (*Panel A*) and without (*Panel B*) options that are double sorted based on different characteristics and MAX(10). Specifically, we report excess returns of quintile MAX portfolios after controlling for different characteristics such as momentum (MOM), reversals (REV), illiquidity (ILLIQ), size, book to market ratio (B/M), idiosyncratic volatility (IVOL), idiosyncratic skewness (ISKEW) and institutional ownership (IOR). We also report the corresponding alphas of the Five-factor Fama and French (2014) model. Excess returns are expressed in percentage points and all portfolios are value-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, Compustat and OptionMetrics IvyDB database and contain monthly series from January 1996 to August 2015.

Panel A: Stocks with options

Characteristics	Low MAX	2	3	4	High MAX	HML	FF5 Alpha
MOM	0.97	0.59	0.56	0.30	-0.04	-1.01	-0.78
	[3.62]	[1.87]	[1.54]	[0.65]	[-0.07]	[-2.44]	[-3.49]
REV	0.59	0.64	0.56	0.48	0.35	-0.24	-0.12
	[2.22]	[1.94]	[1.44]	[0.92]	[0.52]	[-0.44]	[-0.48]
ILLIQ	0.91	0.68	0.54	0.20	0.15	-0.75	-0.44
	[2.94]	[2.08]	[1.45]	[0.43]	[0.24]	[-1.55]	[-2.07]
SIZE	1.05	0.88	0.62	0.38	0.08	-0.97	-0.61
	[3.19]	[2.49]	[1.58]	[0.79]	[0.12]	[-1.99]	[-2.93]
B/M	0.82	0.62	0.52	0.23	0.21	-0.61	-0.52
	[3.15]	[2.05]	[1.42]	[0.46]	[0.36]	[-1.39]	[-2.11]
IVOL	0.71	0.52	0.52	0.42	0.35	-0.36	-0.25
	[1.98]	[1.37]	[1.21]	[0.97]	[0.64]	[-1.04]	[-0.83]
ISKEW	0.79	0.69	0.37	0.49	0.19	-0.60	-0.34
	[3.04]	[2.28]	[1.01]	[0.95]	[0.29]	[-1.15]	[-1.39]
IOR	0.80	0.74	0.58	0.54	0.32	-0.48	-0.21
	[2.95]	[2.35]	[1.57]	[1.09]	[0.49]	[-0.90]	[-0.86]

Panel B: Stocks without Options

Characteristics	Low MAX	2	3	4	High MAX	HML	FF5 Alpha
MOM	1.00	0.71	0.53	0.15	-0.08	-1.08	-0.78
	[3.03]	[1.80]	[1.27]	[0.28]	[-0.13]	[-2.24]	[-2.88]
REV	0.85	0.76	0.77	0.51	-0.12	-0.97	-0.64
	[3.02]	[2.07]	[1.76]	[0.88]	[-0.15]	[-1.47]	[-2.12]
ILLIQ	1.08	0.75	0.59	0.29	-0.14	-1.22	-0.90
	[3.57]	[2.19]	[1.48]	[0.60]	[-0.20]	[-2.15]	[-3.40]
SIZE	1.20	1.11	0.99	0.76	0.09	-1.10	-0.82
	[3.73]	[2.85]	[2.15]	[1.39]	[0.12]	[-1.94]	[-2.95]
B/M	1.00	0.74	0.83	0.29	0.00	-1.00	-0.81
	[3.91]	[2.11]	[1.99]	[0.57]	[0.00]	[-1.75]	[-2.97]
IVOL	1.11	0.66	0.77	0.40	-0.02	-1.13	-1.04
	[2.43]	[1.43]	[1.61]	[0.75]	[-0.04]	[-3.24]	[-3.39]
ISKEW	0.99	0.65	0.56	0.51	-0.11	-1.10	-0.66
	[3.75]	[1.90]	[1.34]	[0.85]	[-0.14]	[-1.61]	[-2.18]
IOR	1.02	0.74	0.78	0.89	0.15	-0.87	-0.57
	[4.03]	[2.42]	[1.94]	[1.72]	[0.19]	[-1.33]	[-2.00]

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 median 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).

Option Illiquidity (ILLIQ): We measure options liquidity in the same way as the Amihud measure for stock liquidity. We divide the difference in the bid and ask prices by the call premium.

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.

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 et al. (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 (2000), we define the idiosyncratic skewness of stock i in month t as the skewness of daily residuals during the previous 3 months.

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_i(R_{m,d} - r_{f,d}) + \gamma_i(R_{m,d} - r_{f,d})^2 + \nu_{i,d}, \tag{9}$$

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:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_{1,i}(R_{m,d} - r_{f,d}) + \beta_{2,i}HML_d + \beta_{3,i}SMB_d + \varepsilon_{i,d}, \tag{10}$$

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: $IVOL_{i,t} = \sqrt{var(\varepsilon_{i,d})}$.

Option Illiquidity (ILLIQ): Following Amihud (2002), we measure liquidity for each stock as the ratio of the absolute monthly stock return to its dollar trading volume.

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.

Internet Appendix to

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

by

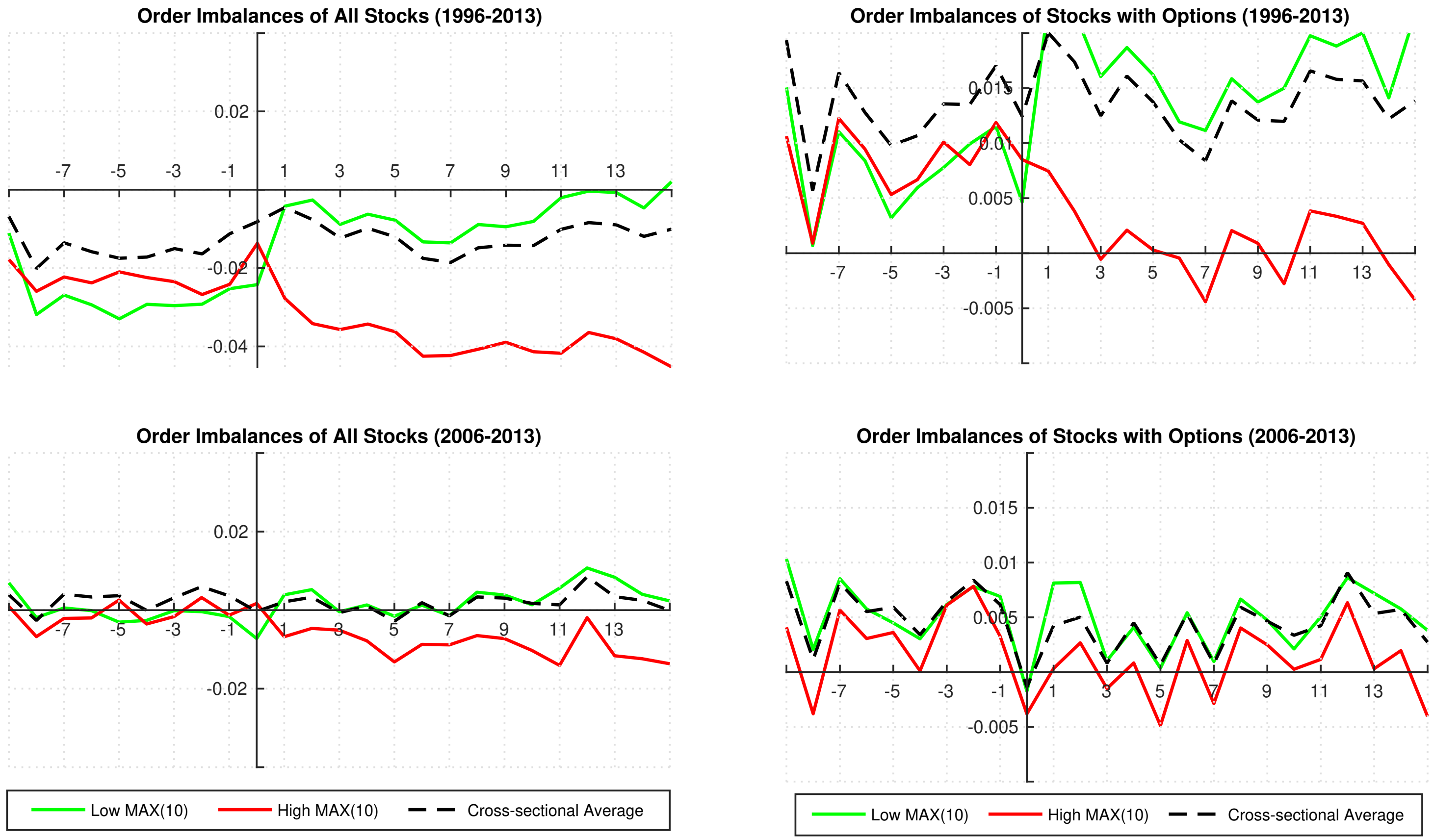
Ilias Filippou   Pedro A. Garcia-Ares   Fernando Zapatero

(Not for publication)

Table A1 provides mean returns of decile portfolios of options sorted on the previous 10-day maximum return (e.g., MAX(10)) or the option ex-ante skewness (BV-SKEW) following Boyer and Vorkink (2014). Those two sorting variables resemble the fundamental anchor of lottery stocks and options respectively. *Panel A* reports average option returns of the different strategies and *Panel B* the corresponding stock returns. We also display alphas of the Fama and French (2014) five-factor model only 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). Options returns are equally-weighted and stock returns are value-weighted.

Consistently with Byun and Kim (2016), we find that ATM options sorted on a 10-day maximum return of the underlying stock tend be more *overvalued* as the MAX of the stock increases. This is clear from the negative and statistically significant options return obtained from a spread portfolio that goes long the high MAX option portfolio and goes short the low MAX portfolio. However, the returns in *Panel B* of table A1 of long-short portfolios of stocks based on MAX are not statistically significant. Overall, this indicates that at-the-money options substitute for lottery stocks as a strategy for investors with gambling preferences. Interestingly, we find in *Panel A* of table A1 that DOTM options tend to be more *undervalued* as the MAX of the underlying security increases. Specifically, we observe a reverse pattern in comparison to the case of ATM options. Particularly, the returns of lottery options almost monotonically *increase* with MAX rendering a positive and statistically significant return. Thus, the spread portfolio between high and low MAX-sorted options is positive and statistically significant. That is, investors appear to pay a premium for deep-out-of-the-money options whose stocks had the lowest maximum 10-day returns (bottom decile) in the previous month. In this case, it seems that trading in deep-out-the-money calls fills a void in the set of lottery stocks (i.e., complements other lottery strategies).

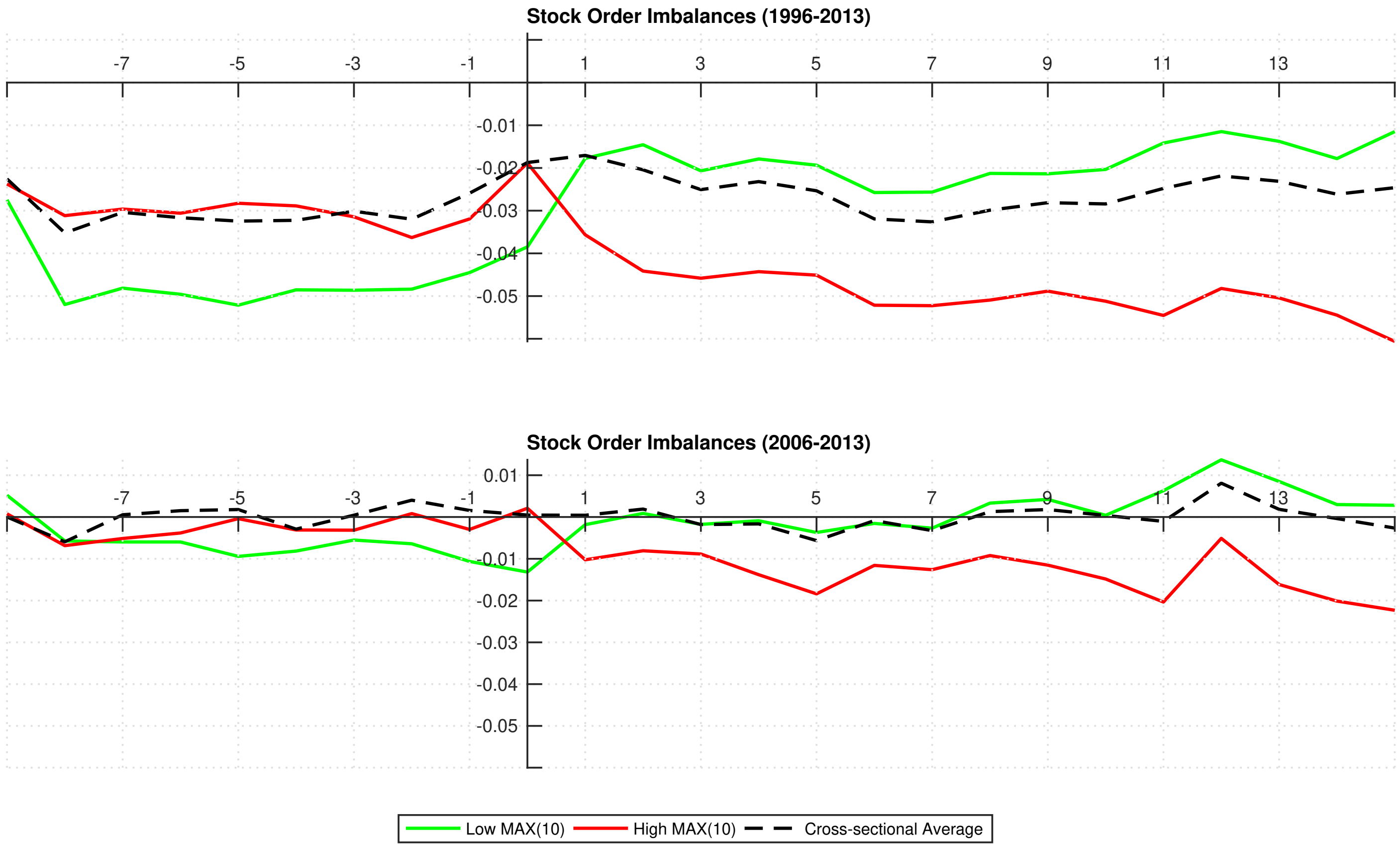
Figure A1. ***Order Imbalances Around the Formation Period***



(a) ***All stocks (with options) and Options***

The figure displays order imbalances of all the available stocks in our sample as well as stocks with options (graph a.) sorted on MAX(10) (e.g., stock with the highest maximum daily return over the previous month). In graph b we offer the corresponding results for stocks without options. We report equal-weighted average order imbalance from nine trading days prior to the sorting date until 15 trading days after the sorting date. The cross-sectional average corresponds to the average order imbalance of all the assets or interest (e.g., across stocks or options) on each day. The data are collected from TAQ and contain daily series from January 1996 to December 2013.

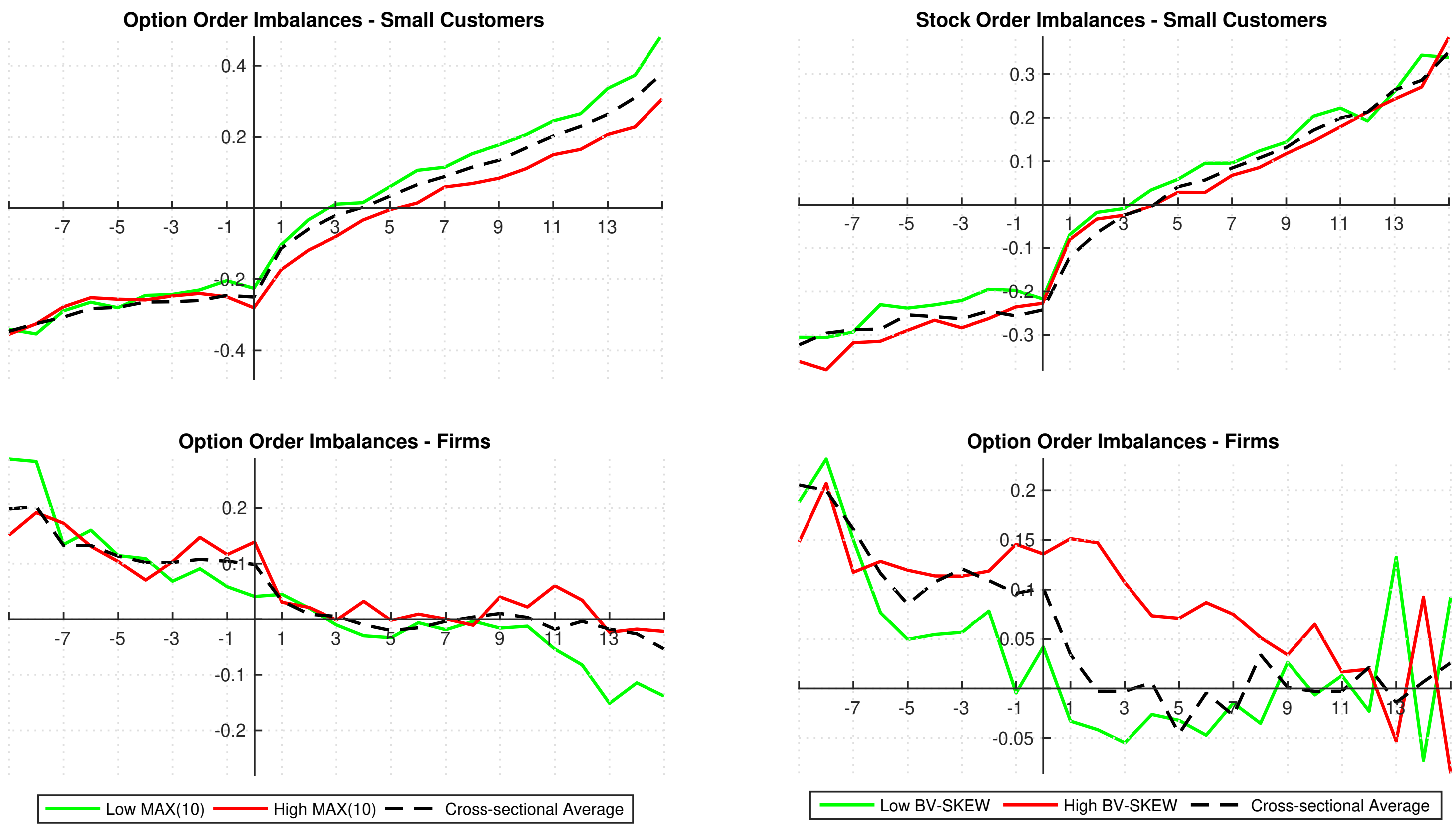
Figure A1. ***Order Imbalances Around the Formation Period*** *(continued)*



(b) ***All stocks without Options***

The figure displays order imbalances of all the available stocks in our sample as well as stocks with options (graph a.) sorted on MAX(10) (e.g., stock with the highest maximum daily return over the previous month). In graph b we offer the corresponding results for stocks without options. We report equal-weighted average order imbalance from nine trading days prior to the sorting date until 15 trading days after the sorting date. The cross-sectional average corresponds to the average order imbalance of all the assets or interest (e.g., across stocks or options) on each day. The data are collected from TAQ and ISE and contain daily series from January 1996 to December 2013.

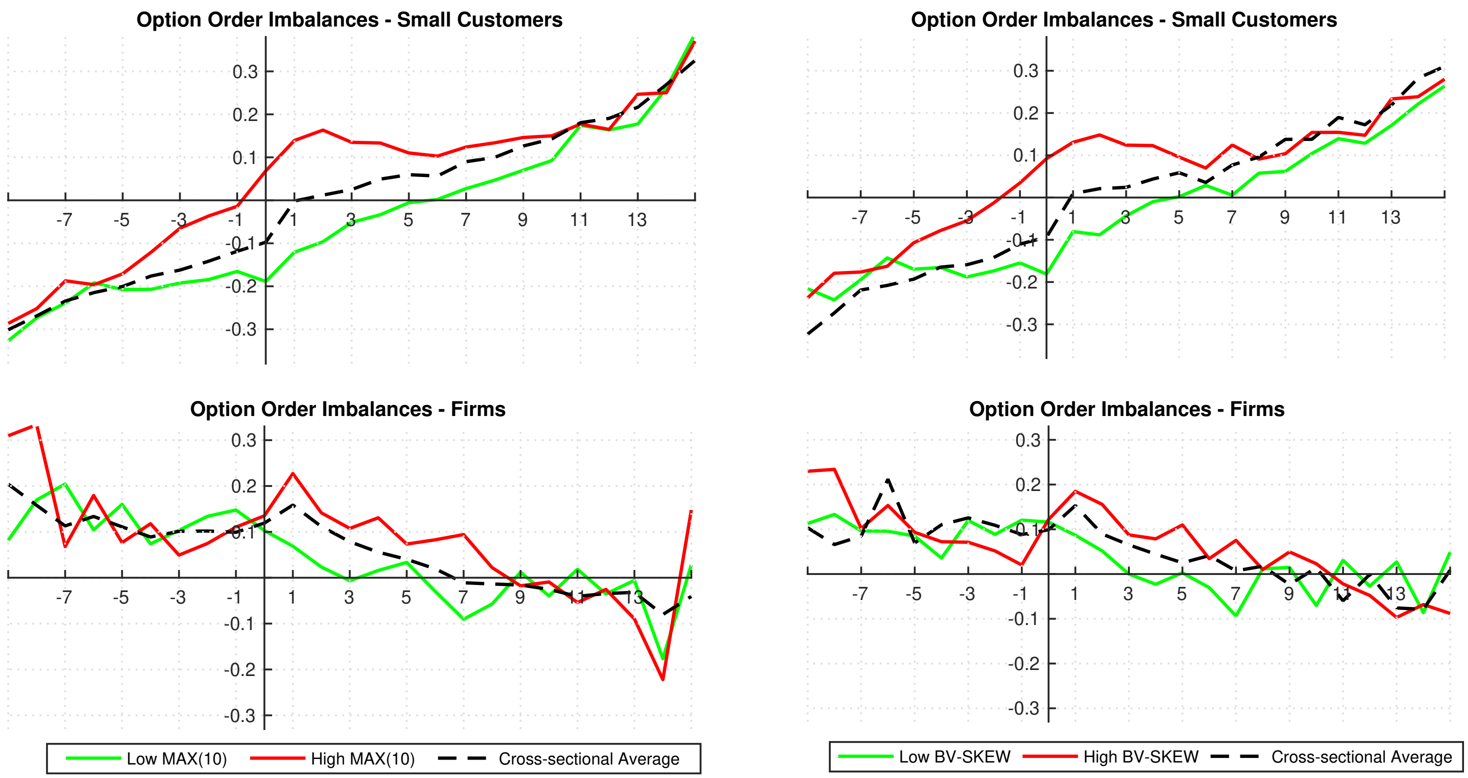
Figure A2. *Disaggregated Order Imbalances Around the Formation Period*



(a) ***At-the-Money Options***

The figure displays small customer and firm-level order imbalances of options sorted on MAX(10) (e.g., stock with the highest maximum daily return over the previous month) and BV-SKEW. We report equal-weighted average order imbalance from nine trading days prior to the sorting date until 15 trading days after the sorting date. The cross-sectional average corresponds to the average order imbalance of all the assets or interest (e.g., across stocks or options) on each day. We offer results for at-the-money, out-of-the-money and deep-out-of-the-money options and their corresponding stocks. The data are collected from TAQ and ISE and contain daily series from January 2006 to December 2013.

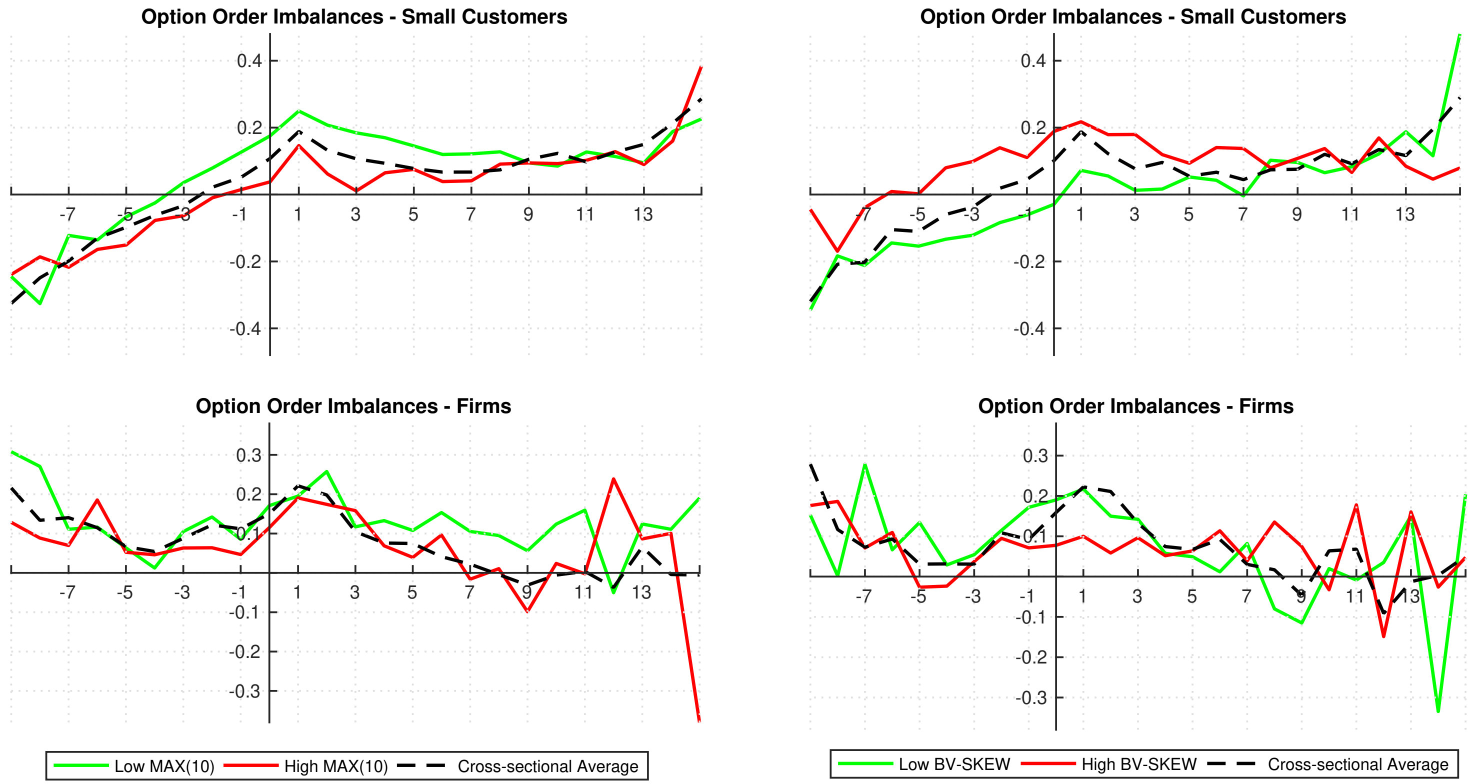
Figure A2. ***Disaggregated Order Imbalances Around the Formation Period*** *(continued)*



(b) ***Out-of-the-Money Options***

The figure displays small customer firm-level order imbalances of stocks and options sorted on MAX(10) (e.g., stock with the highest maximum daily return over the previous month) and BV-SKEW. We report equal-weighted average order imbalance from nine trading days prior to the sorting date until 15 trading days after the sorting date. The cross-sectional average corresponds to the average order imbalance of all the assets or interest (e.g., across stocks or options) on each day. We offer results for at-the-money, out-of-the-money and deep-out-of-the-money options and their corresponding stocks. The data are collected from TAQ and ISE and contain daily series from January 2006 to December 2013.

Figure A2. ***Disaggregated Order Imbalances Around the Formation Period*** *(continued)*



(c) ***Deep-Out-of-the-Money Options***

The figure displays small customer and firm-level order imbalances of stocks and options sorted on MAX(10) (e.g., stock with the highest maximum daily return over the previous month) and BV-SKEW. We report equal-weighted average order imbalance from nine trading days prior to the sorting date until 15 trading days after the sorting date. The cross-sectional average corresponds to the average order imbalance of all the assets or interest (e.g., across stocks or options) on each day. We offer results for at-the-money, out-of-the-money and deep-out-of-the-money options and their corresponding stocks. The data are collected from TAQ and ISE and contain daily series from January 2006 to December 2013.

Table A1. Options Sorted on Lottery Features

This table presents portfolios of options sorted based on different intervals of moneyness. *Panel A* show results of options sorted on MAX or BV-SKEW. *Panel A* (*Panel B*) display results for option (stock) returns. We also report the corresponding alphas of the Five-factor Fama and French (2014) model. Excess 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 August 2015.

Panel A: Option Returns

Lottery Features	Low	2	3	4	5	6	7	8	9	High	HML	FF5 Alpha
						At-the-money Options						
BV-SKEW	0.02	0.05	0.05	0.05	0.07	0.06	0.04	0.01	0.08	0.08	0.06	0.01
	[0.63]	[1.36]	[1.37]	[1.25]	[1.64]	[1.28]	[0.96]	[0.31]	[1.54]	[1.49]	[1.63]	[0.27]
MAX(10)	0.12	0.10	0.11	0.08	0.07	0.04	0.02	0.02	0.00	-0.03	-0.15	-0.09
	[2.55]	[2.05]	[2.27]	[1.79]	[1.62]	[0.78]	[0.41]	[0.38]	[0.09]	[-0.72]	[-3.37]	[-2.78]
						Out-of-the-money Options						
BV-SKEW	-0.01	-0.05	-0.01	0.02	0.04	0.07	-0.02	0.02	0.02	0.03	0.04	0.04
	[-0.14]	[-0.79]	[-0.12]	[0.28]	[0.59]	[1.09]	[-0.24]	[0.26]	[0.31]	[0.42]	[0.45]	[0.45]
MAX(10)	0.01	0.05	0.00	0.07	0.02	0.04	-0.01	-0.04	0.00	-0.05	-0.06	-0.06
	[0.12]	[0.68]	[0.06]	[1.06]	[0.24]	[0.57]	[-0.22]	[-0.62]	[0.06]	[-0.89]	[-0.73]	[-0.73]
						Deep-out-of-the-money Options						
BV-SKEW	-0.04	-0.10	-0.01	-0.15	-0.12	-0.22	-0.25	-0.23	-0.42	-0.66	-0.63	-0.62
	[-0.41]	[-0.98]	[-0.07]	[-1.90]	[-1.58]	[-3.15]	[-3.20]	[-2.44]	[-6.21]	[-17.33]	[-6.34]	[-6.12]
MAX(10)	-0.37	-0.19	-0.29	-0.28	-0.19	-0.18	-0.28	-0.10	-0.20	-0.10	0.27	0.33
	[-5.04]	[-1.91]	[-6.01]	[-5.55]	[-2.95]	[-2.01]	[-4.01]	[-1.09]	[-1.97]	[-0.90]	[2.31]	[2.68]

Panel B: Stock Returns

Lottery Features	Low	2	3	4	5	6	7	8	9	High	HML	FF5 Alpha
						At-the-money Options						
BV-SKEW	0.41	0.66	0.60	0.72	0.68	0.56	0.49	0.43	0.41	0.82	0.40	0.18
	[1.53]	[1.99]	[1.98]	[1.94]	[1.90]	[1.41]	[1.29]	[1.17]	[1.04]	[2.20]	[1.45]	[0.52]
MAX(10)	0.82	0.68	0.80	0.49	0.37	0.39	0.49	0.51	0.16	0.31	-0.51	-0.20
	[3.01]	[2.41]	[3.08]	[1.52]	[1.00]	[1.06]	[1.02]	[0.95]	[0.27]	[0.39]	[-0.73]	[-0.53]
						Out-of-the-money Options						
BV-SKEW	1.03	0.42	0.65	0.43	0.35	0.69	0.37	0.38	0.96	0.84	-0.19	-0.44
	[1.77]	[0.80]	[1.39]	[0.98]	[0.76]	[1.64]	[0.84]	[1.01]	[2.77]	[2.91]	[-0.41]	[-1.08]
MAX(10)	0.69	0.93	0.74	0.49	0.22	0.55	0.70	0.50	0.36	0.33	-0.37	0.12
	[2.40]	[3.21]	[2.39]	[1.33]	[0.58]	[1.34]	[1.33]	[0.83]	[0.53]	[0.39]	[-0.50]	[0.26]
						Deep-out-of-the-money Options						
BV-SKEW	1.03	0.76	0.72	0.88	0.42	0.40	0.30	0.79	0.70	0.86	-0.17	-0.17
	[1.87]	[1.27]	[1.31]	[1.74]	[0.87]	[0.87]	[0.63]	[1.69]	[1.70]	[2.10]	[-0.37]	[-0.32]
MAX(10)	0.96	0.66	1.20	0.27	0.78	0.29	0.43	0.58	0.54	-0.12	-1.08	-0.69
	[2.82]	[1.58]	[2.93]	[0.65]	[1.66]	[0.53]	[0.73]	[0.88]	[0.64]	[-0.14]	[-1.53]	[-1.40]

Table A2. Double Sorts - 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 dependent 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). P-values are in parenthesis. The data is collected from CRSP and OptionMetrics IvyDB database contain monthly series from January 1996 to August 2015.

Panel A: Option Returns

	At-the-money Options			*Out-of-the-money Options*			*Deep-out-of-the-money Options*		
	Low MAX	2	High MAX	Low MAX	2	High MAX	Low MAX	2	High MAX
$HML^{BV-SKEW}$	0.05	0.00	-0.03	0.03	-0.01	0.02	-0.52	-0.31	-0.25
	[1.78]	[-0.16]	[-0.85]	[0.45]	[-0.20]	[0.36]	[-6.18]	[-3.28]	[-2.92]
	Low BV-SKEW	2	High BV-SKEW	Low BV-SKEW	2	High BV-SKEW	Low BV-SKEW	2	High BV-SKEW
$HML^{MAX(10)}$	-0.06	-0.14	-0.15	-0.12	-0.03	0.00	-0.04	-0.14	0.12
	[-1.87]	[-3.86]	[-4.17]	[-2.27]	[-0.54]	[0.01]	[-0.44]	[-1.60]	[1.36]

Panel B: Stock Returns

	At-the-money Options			*Out-of-the-money Options*			*Deep-out-of-the-money Options*		
	Low MAX	2	High MAX	Low MAX	2	High MAX	Low MAX	2	High MAX
$HML^{BV-SKEW}$	0.17	-0.11	-0.83	0.22	-0.64	-0.81	0.35	-0.75	-0.40
	[1.15]	[-0.48]	[-1.98]	[1.06]	[-2.05]	[-1.58]	[1.28]	[-2.29]	[-1.03]
	Low BV-SKEW	2	High BV-SKEW	Low BV-SKEW	2	High BV-SKEW	Low BV-SKEW	2	High BV-SKEW
$HML^{MAX(10)}$	0.09	-0.57	-1.28	-0.46	-0.24	-0.74	-0.25	-0.69	-1.01
	[0.23]	[-1.35]	[-2.20]	[-0.92]	[-0.60]	[-2.01]	[-0.47]	[-1.40]	[-2.11]

Table A3. Lottery Stock and Option Characteristics

This table reports the difference of time-series average of the median firm characteristics across stocks and options between the extreme deciles of MAX(10) and BV-SKEW portfolios. MAX(10) represents the 10-day maximum daily stock return over previous month and BV-SKEW is the Boyer and Vorkink (2014) measure of ex ante skewness of call options. *Panel A* (*Panel B*) shows results of options (stock) characteristics. Specifically, *Panel A* reports results the differences in options characteristics between the extreme lottery decile portfolios comprising the ex ante skewness (BV-SKEW); the implied volatility (IMP VOL); the call premium (CALL PRE); the deltas (DELTA); the illiquidity (ILLIQ); the dollar volume (DOL VOL); and the moneyness (X/S). The differences in stock characteristics of the extreme lottery portfolios include the idiosyncratic skewness (ISKEW); the idiosyncratic volatility (IVOL); reversals (REV); momentum (MOM); turnover; the book-to-market ratio (B/M); the average price; the market capitalisation (SIZE, in millions); the debt-to-assets ratio; the institutional ownership (IOR); the stock volume; the illiquidity (ILLIQ) and the average MAX return. The estimation is based on the rebalancing date and we are focusing on 1-month call options. We show results for three categories of moneyness, namely, at-the-money (ATM) call options (e.g., options in the range of $0.90 < X/S < 1.10$ with moneyness close to 1), out-of-the- money call options (OTM) (e.g., options in the range of $1 < X/S < 1.10$ with moneyness close to 1.10) and deep out-of-the money call options (DOTM) (e.g., options with the highest moneyness in the interval $X/S > 1.10$). 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, Compustat and OptionMetrics IvyDB database and contain monthly series from January 1996 to August 2015.

Panel A: Option Characteristics

Lottery Features	BV-SKEW	IMP VOL	CALL PRE	DELTA	OVOL	ILLIQ	OI	DOL VOL	X/S
					At-the-money Options				
BV-SKEW	3.45	0.08	-1.68	-0.45	3.49	0.32	105.22	-1.14	0.10
	41.48	5.63	-37.16	-32.39	5.75	19.19	5.54	-1.85	43.24
MAX(10)	-0.20	0.34	0.33	0.01	21.08	-0.01	73.09	30.63	0.00
	-4.41	20.26	3.27	2.55	10.04	-1.38	2.05	6.86	1.61
					Out-of-the-money Options				
BV-SKEW	7.46	-0.17	-0.44	-0.15	-11.68	0.31	689.04	-16.64	0.02
	12.33	-17.94	-7.05	-27.61	-4.65	15.66	6.91	-4.64	25.83
MAX(10)	-3.99	0.31	0.54	0.16	26.72	-0.31	-372.36	28.09	0.00
	-12.56	16.82	4.83	42.36	7.95	-24.20	-4.23	5.93	7.51
					Deep-out-of-the-money Options				
BV-SKEW	81.23	0.05	-0.19	-0.12	-2.54	0.28	584.44	-1.62	0.13
	5.54	2.79	-6.93	-26.38	-3.15	7.44	7.79	-3.21	10.72
MAX(10)	-14.32	0.30	0.10	0.07	5.19	-0.16	-446.32	1.62	0.06
	-8.53	17.04	8.04	19.55	5.38	-6.63	-6.50	6.34	8.51

Panel B: Stock Characteristics

Lottery Features	ISKEW	IVOL	REV	MOM	TURNOVER	B/M	PRICE	SIZE	D/A	IOR	SVOL	ILLIQ	MAX
							At-the-money Options						
BV-SKEW	-0.53	0.00	-0.09	-0.14	0.43	0.07	-8.84	-1.05	-0.03	0.01	0.04	0.00	0.00
	-15.62	6.94	-13.05	-10.80	12.03	4.25	-11.25	-10.40	-4.03	1.57	1.95	1.96	-0.85
MAX(10)	0.53	0.03	0.21	0.18	2.63	-0.14	-18.40	-5.20	-0.15	-0.02	-0.21	0.00	0.03
	15.87	20.94	17.79	2.98	33.03	-4.58	-10.04	-10.98	-12.21	-1.61	-2.63	-1.36	18.74
							Out-of-the-money Options						
BV-SKEW	-0.98	-0.01	-0.15	-0.41	-1.60	0.15	9.22	9.32	0.08	-0.02	0.95	0.00	-0.02
	-14.05	-22.54	-15.78	-11.82	-25.07	8.92	3.41	6.72	8.80	-2.76	5.86	1.92	-23.70
MAX(10)	0.53	0.03	0.21	0.23	2.97	-0.10	-19.29	-7.95	-0.12	-0.02	-0.19	0.00	0.03
	13.05	20.31	18.03	3.36	32.83	-3.51	-8.41	-10.93	-9.27	-1.74	-3.39	-1.17	18.28
							Deep-out-of-the-money Options						
BV-SKEW	-0.98	-0.01	-0.18	-0.37	-0.88	0.06	13.16	4.03	0.04	0.03	7.47	0.00	-0.02
	-15.05	-13.35	-16.90	-11.43	-7.55	3.76	5.80	6.78	3.52	5.25	7.09	0.66	-23.92
MAX(10)	0.61	0.03	0.26	0.22	3.44	-0.10	-17.75	-4.76	-0.10	-0.10	-0.17	0.00	0.04
	13.63	22.63	24.64	3.31	40.25	-3.12	-9.86	-7.91	-7.17	-8.14	-2.36	-1.51	21.53

Table A4. Commonality of Lottery Portfolios

This table presents the percentage of stocks that are in common in portfolios of stock sorted on MAX(10) or BV-SKEW. *Panel A* reports the percentage of stocks that are common in the extreme MAX and BV-SKEW portfolios conditional on the option moneyness (e.g., at-the-money options (ATM), out-of-the-money options (OTM) and deep-out-of-the-money options (DOTM)). *Panel B* shows the commonality of stocks in extreme MAX(10) and BV-SKEW portfolios across ATM, OTM and DOTM bins. The data is collected from CRSP and OptionMetrics IvyDB database and contain monthly series from January 1996 to August 2015.

Panel A: Commonality in Lottery Stocks and Options

Lottery feature	Low MAX	High MAX	Low MAX	High MAX	Low MAX	High MAX
	Stocks with ATM options		*Stocks with OTM options*		*Stocks with DOTM options*	
Low BV-SKEW	0.18	0.00	0.00	0.00	0.00	0.00
High BV-SKEW	0.03	0.05	0.37	0.00	0.32	0.02

Panel B: Commonality of stocks in option bins of high MAX or BV-SKEW portfolios

Option bin	% of stocks with ATM options	% of stocks with OTM options	% of stocks with DOTM options	% of stocks with ATM options	% of stocks with OTM options	% of stocks with DOTM options
		MAX(10)			*BV-SKEW*	
Stocks with ATM options	1.00	0.93	0.81	1.00	0.29	0.20
Stocks with OTM options	0.34	1.00	0.28	0.11	1.00	0.15
Stocks with DOTM options	0.31	0.29	1.00	0.08	0.16	1.00

Table A5. Lottery Assets and Shorting Fees

This table presents the median of the average short interest and shorting fee of stocks sorted based on MAX(10) and BV-SKEW. *Panel A* shows results based on single sorts of stocks with and without options on MAX(10) and BV-SKEW and *Panel* presents the corresponding results of dependent and independent double-sorts on MAX(10) and BV-SKEW and *vice versa* (*Panel C*). We also display Newey and West (1987) t-statistics is squared brackets corrected for autocorrelation and heteroskedasticity. The data is collected from CRSP and OptionMetrics IvyDB database and contain monthly series from January 1996 to August 2015.

Panel A: Univariate Sorts

Spread portfolios	Low MAX	High MAX	HML	Low BV-SKEW	High BV-SKEW	HML
			Stocks with at-the-money options			
Shorting Fee	3.12	9.03	5.91	4.14	5.13	0.99
	[23.13]	[14.88]	[11.59]	[14.92]	[13.40]	[5.12]
			Stocks with out-of-the-money options			
Shorting Fee	2.97	9.42	6.45	7.32	2.92	-4.41
	[25.00]	[14.77]	[11.63]	[14.67]	[25.77]	[-10.27]
			Stocks with deep-out-of-the-money options			
Shorting Fee	4.40	12.37	7.97	8.90	5.60	-3.29
	[17.08]	[16.27]	[13.07]	[15.57]	[14.52]	[-7.58]
		Stocks without options				
Shorting Fee	1.59	4.16	2.56			
	[10.49]	[15.61]	[10.64]			

Panel B: Double sorts on BV-SKEW and MAX(10)

	Dependent Sorts			Independent Sorts		
Spread portfolios	Low MAX	2	High MAX	Low MAX	2	High MAX
			Stocks with at-the-money options			
$HML^{BV-SKEW}_{Shorting\ Fee}$	0.01	0.01	0.02	0.01	0.01	0.02
	[4.44]	[5.30]	[6.64]	[4.57]	[5.35]	[6.54]
			Stocks with out-of-the-money options			
$HML^{BV-SKEW}_{Shorting\ Fee}$	-0.01	-0.01	-0.01	-0.02	-0.01	0.00
	[-6.12]	[-6.59]	[-5.88]	[-8.46]	[-6.74]	[-0.04]
			Stocks with deep-out-of-the-money options			
$HML^{BV-SKEW}_{Shorting\ Fee}$	-0.01	0.00	0.01	-0.02	0.00	0.02
	[-5.69]	[-0.78]	[3.08]	[-6.60]	[-0.23]	[5.48]

Panel C: Double sorts on MAX(10) and BV-SKEW

	Dependent Sorts			Independent Sorts		
Spread portfolios	Low BV-SKEW	2	High BV-SKEW	Low BV-SKEW	2	High BV-SKEW
			Stocks with at-the-money options			
$HML^{MAX}_{Shorting\ Fee}$	0.03	0.04	0.04	0.03	0.04	0.04
	[10.29]	[11.48]	[10.98]	[10.40]	[11.06]	[10.98]
			Stocks with out-of-the-money options			
$HML^{MAX}_{Shorting\ Fee}$	0.04	0.03	0.02	0.03	0.03	0.05
	[10.20]	[11.15]	[9.11]	[9.33]	[10.72]	[10.75]
			Stocks with deep-out-of-the-money options			
$HML^{MAX}_{Shorting\ Fee}$	0.04	0.04	0.04	0.03	0.05	0.07
	[11.77]	[10.24]	[11.38]	[6.22]	[9.83]	[11.98]