Searching for Gambles:
Investor Attention, Gambling Sentiment, and Stock Market Outcomes*

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Abstract - This paper examines whether shifts in gambling attitudes affect stock market outcomes. We use the Internet search volume for lottery-related keywords to capture changes in gambling sentiment. When the overall gambling sentiment is high, (i) stocks with lottery-like characteristics earn positive abnormal returns in the short-run, (ii) investors increase aggregate demand for lottery-like stocks, (iii) managers are more likely to announce stock splits to cater to an increased demand for low-priced lottery stocks, and (iv) IPOs perceived as lotteries earn higher first-day returns. These results suggest that shifts in overall gambling attitudes have a spillover effect on the stock market.

JEL classifications: G11; G12; G14

Keywords: Gambling attitudes; investor attention; catering; stock splits; IPO underpricing; lottery-type stocks.

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Abstract - This paper examines whether shifts in gambling attitudes affect stock market outcomes. We use the Internet search volume for lottery-related keywords to capture changes in gambling sentiment. When the overall gambling sentiment is high, (i) stocks with lottery-like characteristics earn positive abnormal returns in the short-run, (ii) investors increase aggregate demand for lottery-like stocks, (iii) managers are more likely to announce stock splits to cater to an increased demand for low-priced lottery stocks, and (iv) IPOs perceived as lotteries earn higher first-day returns. These results suggest that shifts in overall gambling attitudes have a spillover effect on the stock market.

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1. Introduction

An emerging literature in finance examines the potential link between gambling behavior and financial market outcomes. In particular, recent theoretical studies predict that investors would be willing to accept a negative return premium for stocks with positively-skewed returns (e.g., Shefrin and Statman, 2000; Brunnermeier, Gollier, and Parker, 2007; Mitton and Vorkink, 2007; Barberis and Huang, 2008). Stocks with lottery-like return distribution get temporarily overpriced and earn a negative average risk-adjusted return in the long-run. Empirical research on the effects of gambling attitudes has typically focused on the cross-sectional variation in gambling preferences and their impact on financial market outcomes (e.g., Bali, Cakici, and Whitelaw, 2011; Kumar, Page, and Spalt, 2011). For example, Kumar, Page, and Spalt (2011) find that investors' gambling preferences vary geographically impact stock returns as well as corporate policies.

In this paper, we study how the time-variation in overall gambling attitudes affects various stock market outcomes. We posit that attention to low-probability payoffs in one setting may motivate individuals to overweight low-probability events in other economic settings. Specifically, we conjecture that an increase in gambling sentiment is likely to induce price pressure on stocks with lottery-like characteristics. Consequently, if arbitrage costs are high, the return of these stocks would be predictable in the short-run. Further, corporate financial decisions would be affected as firms respond to changes in investors' gambling attitudes and their impact on asset prices.

To test these conjectures, we develop a novel measure of gambling sentiment of investors using Google's search volume intensity (*SVI*) for lottery-related keywords. We start by examining the effects of gambling sentiment on stock returns. We focus on a segment of the U.S. stock market in which stocks have lottery-like return distributions. Following Kumar, Page, and

Spalt (2014), we define lottery-like stocks as those with low nominal share prices, high idiosyncratic skewness, and high idiosyncratic volatility. These stocks are also associated with low average returns, high return volatility and high turnover (Scheinkman and Xiong, 2003; Hong, Scheinkman, and Xiong, 2006; Grinblatt and Keloharju, 2009; Dorn and Sengmueller, 2009). We conjecture that lottery-like stocks are likely to be more affected by gambling sentiment than non-lottery stocks. Specifically, when gambling sentiment is stronger, investors' demand for lottery-like stocks would increase. If arbitrage costs are high,[1] this excess demand in turn could generate price pressure on lottery-like stocks and lead to positive abnormal return in the short-run.

Consistent with our prediction, we find that when gambling sentiment of investors becomes stronger, lottery-like stocks earn positive abnormal returns in the following month. In economic terms, a one standard deviation increase in investors' gambling sentiment is associated with an abnormal return of 47 basis points for the lottery-like stock portfolio in the following month. Further, this positive abnormal return is eventually arbitraged away within three months.

Next, we use attention-grabbing lottery jackpots to identify the source of time-variation in investors' gambling attitudes. Jackpot announcements are exogenous, attention-grabbing events that are likely to generate excitement among investors who may gamble in the stock market. Consistent with our expectation, we find abnormal stock returns among lottery-like stocks around these jackpots. The average abnormal return from month -1 to month +1 is 1.7% per month. In addition, during this period, the average abnormal trading volume is 17.2%.

To study investors' demand for lottery-like stocks more directly, we use trading data of a major U.S. discount brokerage firm (Barber and Odean, 2000). Consistent with a spillover effect

[1] Given the low prices and high volatility of lottery-type stocks, the costs associated with arbitraging them are likely to be high.

on investor demand, we find positive excess buy-sell imbalance on lottery-like stocks around the largest jackpot during the 1992-1996 period. The average excess buy-sell imbalance from month -1 to month +1 is 7%, which suggests a 7% increase in net purchase of lottery-like stocks relative to non-lottery stocks. Similarly, large drawings are associated with excess buy-sell imbalance of 3% in the next trading day. The spillover effect is consistent with the evidence documented for the betting market (e.g., Scott and Garen, 1994; Calcagno, Walker, and Jackson, 2010).

In the second set of tests, we examine the extent to which geographical differences in gambling sentiment influence the long-term performance of lottery-like stocks. As local investors' gambling sentiment varies across regions (Kumar, Page, and Spalt, 2011), we posit that the effects of gambling sentiment on stock returns would be stronger among U.S. states with stronger gambling sentiment. In these states, lottery-like stocks would be overpriced and are likely to underperform in the long-run. To test our prediction, we use each firm's headquarter state to define its location and use the average state-level *SVI* to measure the gambling sentiment of local investors.

We find that in states with strong gambling sentiment, lottery-like stocks significantly underperform non-lottery stocks (i.e., stocks with high nominal share price, low idiosyncratic skewness, and low idiosyncratic volatility) by 60 basis points per month. The results are stronger for stocks that are smaller or with lower institutional ownership. In contrast, in U.S. states with relatively weak gambling sentiment, lottery-like stocks do not perform differently from non-lottery stocks.

Next, we change our perspective and investigate whether gambling sentiment affects corporate decisions. Low nominal share price is a salient feature of lottery-like stocks. Baker, Greenwood, and Wurgler (2009) show that retail investors' demand for stocks with low nominal share prices is time-varying. Further, firms cater to such demand by splitting stocks with high nominal share prices. We conjecture that the time-varying demand for low-priced stock would be related to the time-variation in investors' gambling attitudes. Consistent with this conjecture, we find that firms with high nominal share prices are more likely to split their shares when investors exhibit stronger gambling sentiment.

In the last set of tests, we examine the effects of gambling sentiment on the first-day returns of initial public offerings (IPOs). These tests are motivated by previous research, which demonstrated that IPOs are often perceived as lottery-like by retail investors (Barberis and Huang, 2008; Green and Hwang, 2011). Further, Loughran and Ritter (2004) show that the magnitude of the average first-day return for IPOs changes over time. We conjecture that IPOs would earn higher first-day returns when investors exhibit stronger gambling sentiment. Consistent with our prediction, we find that a one standard deviation increase in investors' gambling sentiment is associated with a 1.6% increase of the average first-day IPO return in the following month.

Overall, these findings suggest that changes in investors' gambling attitudes have a spillover effect on stock market outcomes. In particular, when investors' gambling sentiment becomes stronger, stocks with lottery-like characteristics earn positive abnormal returns, and firms with high nominal share prices are more likely to split their shares. In addition, initial public offerings earn higher first-day returns during these periods of high gambling sentiment.

Our findings contribute to several strands of finance literature. First, we study the time-variation in investors' gambling attitudes. Recent literature shows that cross-sectional differences in gambling attitudes affect stock returns and corporate decisions (e.g., Bali, Cakici, and Whitelaw, 2011; Kumar, Page, and Spalt, 2011). We find that shifts in gambling attitudes over time also matter.

Second, we provide new evidence on the economic effects of investor attention (e.g., Odean, 1999; Barber and Odean, 2008; Palomino, Renneboog, and Zhang, 2009; Da, Engelberg, and Gao, 2011). We show that salient lottery events trigger strong gambling sentiment, which leads to the predictability of lottery-like stocks.

Third, we add to the literature on the motivation behind stock splits (e.g., Lakonishok and Lev, 1987; Angel, 1997) and provide a new explanation for the time-variation in first-day returns for IPOs (e.g., Loughran and Ritter, 2004). Specifically, we show that firms cater to the time-varying demand for lottery-like characteristics (e.g., low nominal share prices) by splitting stocks with high nominal share prices and that time-variation in investors' gambling sentiment is an important determinant of IPO returns.

The rest of our paper proceeds as follows. Section 2 develops our hypotheses. In Section 3, we describe the data and our methods. Section 4 presents the empirical results and Section 5 concludes.

2. Hypotheses development

We consider four distinct economic settings to study the impact of gambling sentiment on financial market outcomes. In the first setting, we focus on the short-term mispricing and correction pattern among lottery-like stocks. This analysis is motivated by recent studies, which find that investors are more likely to buy stocks that have recently captured their attention (Barber and Odean, 2008). Specifically, Da, Engelberg, and Gao (2011) show that a surge in attention could lead to temporal overpricing and predict short-term return reversals among the set of attention-grabbing stocks. Further, Google's daily search interest by retail investors is likely to capture market-level sentiment (Da, Engelberg, and Gao, 2015).

We extend this insight to lottery-like stocks that provide gambling opportunities to investors in the stock market. Kumar (2009) finds that state lottery players have similar behavior as investors who overweight lottery-like stocks. When investors gamble in the stock market, they are likely to prefer stocks with low nominal share prices, especially those with positive idiosyncratic skewness for the possibility of extreme returns. Investors may also prefer stocks with high idiosyncratic volatility since extreme returns are more likely for these assets.

Kumar, Page, and Spalt (2014) construct a Lottery Index to categorize all stocks in the CRSP universe into lottery-like stocks, non-lottery stocks and other stocks. Lottery-like (non-lottery) stocks are those with low (high) price, high (low) idiosyncratic skewness and high (low) idiosyncratic volatility. Using this definition of lottery-type firms, we posit that when gambling sentiment is strong, investors are likely to invest disproportionally more in lottery-like stocks, leading to positive price pressure on these stocks. To summarize, our first hypothesis states:

H1: Following periods of high gambling sentiment, lottery-like stocks would earn positive abnormal returns in the short-run.

Our second hypothesis focuses on the cross-sectional variation in the impact of shifts in gambling sentiment on stock returns. Barberis and Huang (2008) show that a security's idiosyncratic skewness would be priced. In particular, investors would be willing to accept lower returns for stocks with positive return skewness. Positive skewness could be a particularly important characteristic for investors with strong gambling attitudes. As investors are known to exhibit local bias (e.g., Coval and Moskowitz, 1999; Grinblatt and Keloharju, 2001; Hong, Kubik, and Stein, 2008; Seasholes and Zhu, 2010), the effects of gambling sentiment on stock returns would be stronger for stocks headquartered in states with stronger gambling attitudes. Further, we expect a larger impact on stocks that are more likely to be held by retail investors, i.e. stocks that are smaller or with lower institutional ownership. For stocks located in states with relatively weak gambling attitudes, the negative lottery-like stock premium should be weaker or non-existent.

To summarize, our second hypothesis posits:

H2: The effects of gambling sentiment on stock returns would be stronger in states with stronger gambling attitudes. Further, this impact is likely to be amplified for smaller stocks and firms with lower institutional ownership.

Our third hypothesis relates to managerial response to changes in investors' gambling attitudes and their potential impact on asset prices. Weld, Michaely, Thaler and Benartzi (2009) show that firms keep their nominal share prices in a particular range by conducting stock splits. Baker, Greenwood, and Wurgler (2009) propose a catering theory of nominal share prices to explain this behavior. They find that the demand for low-priced stocks is time-varying and firms with high nominal share prices splits their shares when such demand is high. So far, the literature has not clearly identified what drives the time-varying demand for low-priced stocks.

We posit that the demand for low-priced stocks would at least partially be related to the gambling sentiment of retail investors.[2] Since low nominal share price is a salient feature of lottery-like stocks, stronger gambling sentiment would increase the demand for low-priced stocks and raise their share prices. Firms with high share prices would cater to this excess demand by splitting their shares. In contrast, firms with low nominal share prices would not split their shares.[3]

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[2] We focus on the behavior of retail investors since past studies show that stocks splits are mainly used to attract retail investors (Baker and Gallagher, 1980; Baker and Powell, 1993; Fernando, Krishnamurthy, and Spindt, 1999). Retail investors are more likely to hold low-priced stocks than institutional investors (Lakonishok, Shleifer, and Vishny, 1992; Gompers and Metrick, 2001; Fernando, Krishnamurthy, and Spindt, 2004; Dyl and Elliott, 2006; Kumar and Lee, 2006).

[3] If the low-priced firms split shares, they would face substantial delisting risks. For example, for a firm with share price of $8, below the median share price of the CRSP universe of $14, a typical split ratio of 2 to 1 brings the share price down to $4. Practitioners often believe that firms with share price below $5 to have substantial delisting risk (Market Watch: http://www.marketwatch.com/story/nyse-euronext-seeks-relax-minimum-bid). In addition, firms

To summarize, our third hypothesis is:

H3: Firms with high share prices would exhibit a higher propensity to split their stocks when investors have stronger gambling sentiment.

Our fourth hypothesis relates to another corporate finance anomaly, i.e., IPO underpricing. Loughran and Ritter (2004) show that the initial stock return after IPOs changes over time. The average first-day return doubled from 7% during 1980-1989 to 15% during 1990-1998 and surged to 65% during the 1999-2000 Internet bubble before reverting back to 12% during the 2001-2003 period. IPOs could be perceived as lotteries, given their positively-skewed returns (Barberis and Huang, 2008; Green and Hwang, 2011). Kumar, Page, and Spalt (2011) show that IPOs by firms located in regions with stronger gambling sentiment earn higher first-day returns.

Baker, Greenwood, and Wurgler (2009) show that firms choose a lower nominal offering price for IPOs when investors place relatively higher valuations on low-priced stocks. This raises post-IPO first-day return. Hence the time-variation in the IPO underpricing could be related to investors' gambling sentiment. In particular, if retail investors treat IPOs as lottery-like investment opportunities, they would be willing to pay a higher price for IPOs when their gambling sentiment is strong. This could generate a larger average first-day IPO return.

Overall, we posit that:

H4: The average first-day IPO return would be higher during periods of high gambling sentiment.

3. Data and methodology

cannot easily undo their splits by undertaking reverse splits, as this would give negative signals to the market (e.g., Woolridge and Chambers, 1983; Campbell, Hilscher, and Szilagyi, 2008; Macey, O'Hara, and Pompilio, 2008).

To test these four hypotheses, we collect data from various sources. In this section, we describe the data sets and the measure of gambling sentiment.

3.1. Gambling sentiment

Motivated by Da, Engelberg, and Gao (2011, 2015), we use the search volume intensity (*SVI*) for lottery-related keywords from Google to capture retail investors' gambling sentiment. Specifically, we use *SVIs* for the topic "Lottery" from Google Trends,[4] at both national- and state-levels in the U.S. This includes searches in different languages and different text strings when they are lottery-related.

SVI measures the popularity of a particular search term relative to all other terms from the same location at the same time. An increase in *SVI* indicates that people pay more attention to the topic than they normally do. Google Trends reports *SVI* at weekly frequency. We aggregate this to monthly frequency by linear interpolation as in Da, Engelberg, and Gao (2011).

To study the geographical variation in gambling attitudes, we use the average state-level *SVI* in the previous year to sort all U.S. states and the Washington D.C. into three groups with 17 states or district in each group. State-level *SVIs* are not directly comparable when downloaded separately. We deflate the *SVI* of each state by the corresponding national-level *SVI* to ensure they are comparable cross-searching and across time. We define strong (moderate) (weak) gambling sentiment states as the top (medium) (bottom) 17 states or Washington D.C. as measured by the average *SVI*.

Following Da, Engelberg, and Gao (2011), our main variable is the abnormal search volume intensity (*ASVI*) for the topic "lottery":

[4] Google Trends reports weekly search volume intensity for various keywords. It is available at http://www.google.com/trends/.

$$ASVI_t = LogSVI_t - LogSVI_{t-1}, \qquad (1)$$

where $ASVI_t$ is the abnormal search volume intensity for the topic "lottery" in month *t*. $LogSVI_t$ and $LogSVI_{t-1}$ represent the natural logarithm of *SVI*s in month *t* and month *t-1*, respectively. The time-series of *ASVI* starts from March 2004 and it measures changes in people's attention toward lottery-related events.[5]

3.2. Validation tests

To test whether our measure of gambling sentiment is reasonable, we obtain the state lottery sales data from the North American Association of State and Provincial Lotteries (NASPL). The launch dates of state lotteries are collected from the websites of corresponding states. To calculate the per capital lottery sales data, we obtain the demographics data from the U.S. Census Bureau. Population and education data are based on the 2010 Census. We collect the news data from Factiva.

In the first validation test, we examine whether our measure of gambling sentiment matches with news about state lotteries. Panel A of Figure 1 plots the "lottery" *SVI* for the U.S. By conducting a search on Factiva, we find that nearly all peaks in the series coincide with the dates of the largest lottery jackpots. For example, Points A to H correspond to record-breaking or near-record jackpots. These jackpots are independent of each other and are from two multi-state games, i.e. Mega Millions and Powerball. We use these attention-grabbing jackpots as natural experiments in Section 4.2.

[5] We also use two alternative methods to construct *ASVI*. First, we calculate *ASVI* as the log difference between *SVI* in month *t* and the median of *SVIs* in the previous three months (Da, Engelberg, and Gao, 2011). Second, we regress our baseline *ASVI* measure on month and year dummy variables and use residuals as a robustness check for any potential seasonality effects (Da, Engelberg, and Gao, 2015). We find quantitatively similar results.

Large jackpots receive greater media coverage. A search of lottery related news on Factiva illustrates this. On March 30, 2012, the drawing Friday for the $656 million jackpot, there were 1,045 lottery-related news stories in the U.S. The number of lottery-related news items reduced to 579 on the Friday one month later, almost a 50% drop in one month. This change in media coverage matches with our measure of gambling sentiment.

Next, we analyze how our state-level *SVI* relates to demographic characteristics of local investors. Panel B of Figure 1 depicts the geographical differences in gambling sentiment. It shows that jackpots of single-state lotto games raise mainly the *SVI* in that particular state, while jackpots of multi-state lotto games increase *SVIs* in all states. Panel C reports the regional search interest for each state. It is evident that the Internet search volume for the topic "lottery" is higher in the Western and Eastern coasts and is lower in the Central region.

Table 1 presents the top five and bottom five states during the 2004-2013 period. Florida and Georgia have the highest average *SVIs,* which is consistent with the fact that Powerball (Mega Millions) drawings are based in Florida (Georgia). Further, Massachusetts has one of the highest levels of Catholic concentration and it also has one of the highest average *SVIs*. In contrast, Utah has the highest level of Mormon concentration and it has one of the lowest average *SVIs*. This is consistent with the findings of Kumar, Page, and Spalt (2011) who show that Catholics are more likely to gamble while Mormons have a strong opposition to gambling.

In 2012, the median lottery sales value is $3,834 million for the top gambling sentiment states. This is 27 times greater than that of the bottom states. Obviously, these measures do not account for differences in state population. The median per capita lottery sales is $244 ($136) for the top (bottom) gambling sentiment states. In addition, we observe that the median percentage of the state population over the age of 25 that has a bachelor's degree or higher is 26.5% (29.5%)

for top (bottom) states, which is consistent with Kumar (2009) who shows that education is negatively related to the likelihood of lottery purchases.

Further, all of the top five states have legalized state lotteries. In contrast, three out of the bottom five states have not adopted state lotteries. This is similar to the findings of Kumar, Page, and Spalt (2011) who show that regions with stronger gambling propensity legalize state lotteries earlier. Overall, the results from these validation tests indicate that our measure of gambling sentiment is reasonable.

3.3. Lottery-like stocks

To analyze the influence of retail investors' gambling sentiment on the stock market, we focus on lottery-like stocks for our first two economic settings. Our definition of lottery-like stocks follows that of Kumar, Page, and Spalt (2014), which is a continuous measure of the "lotteriness" of stocks. The measure is based on the theoretical frameworks developed in Harvey and Siddique (2000) and Barberis and Huang (2008) and is also motivated by the empirical definition of lottery-type stocks in Kumar (2009). Specifically, we use three criteria to construct the Lottery Index (LIDX), namely nominal stock price, idiosyncratic skewness and idiosyncratic volatility. Stock price is the closing price in the last trading day of previous calendar year. Idiosyncratic skewness is the third moment of the residual obtained by fitting the following model using daily stock returns in the previous year:

$$r_i - r_f = \alpha + \beta_1(r_{mkt} - r_f) + \beta_2(r_{mkt} - r_f)^2 + \epsilon_t, \tag{2}$$

where r_i is the return of stock i, r_f is the risk free rate, and r_{mkt} is the market return. And, idiosyncratic volatility is the standard deviation of residual from the Carhart (1997) model using daily stock returns in the previous year:

$$r_i - r_f = \alpha + \tilde{\beta}_{mkt}(r_{mkt} - r_f) + \tilde{\beta}_{smb} r_{smb} + \tilde{\beta}_{hml} r_{hml} + \tilde{\beta}_{umd} r_{umd} + \epsilon_i, \tag{3}$$

where r_i is the realized return of stock i, r_f is the risk free rate, and r_{mkt} is the market return. r_{smb}, r_{hml}, *and* r_{umd} are size, market-to-book, and momentum factor returns. We obtain price, return, and market capitalization data at monthly and daily frequencies from the Center for Research on Security Prices (CRSP). The size, market-to-book, and momentum factors are from Kenneth French's data library.[6]

In January of each year, we assign all common stocks (with a share code of 10 or 11) in the CRSP universe into twenty groups based on each criterion. We conduct the three sorting independently and create 60 groups. Group 20 (1) contains the stocks with the highest (lowest) idiosyncratic skewness, highest (lowest) idiosyncratic volatility, or lowest (highest) price. We then add up the group numbers of each stock to a score between 3 and 60 and standardize this score to a value between 0 and 1 using LIDX = (Score-3) / (60-3).[7] Finally, we define lottery-like stocks as stocks with a top 30% LIDX value, non-lottery stocks as those with a bottom 30% LIDX value, and remaining stocks as other stocks. We update this list in January of each year.

Panel A of Table 2 presents the main characteristics of lottery-like stocks. For comparison, we also report the characteristics of non-lottery stocks, other stocks, and all stocks in the CRSP universe. The average price of lottery-like stocks is $5.67, which is comparable in magnitude to the price of lottery tickets.[8] Lottery-like stocks have a small average market capitalization of $266 million. They have higher market-to-book ratio than non-lottery stocks. They also have significantly higher volatility and skewness.

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[6] The risk factors are obtained from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[7] For example, if stock A is in group 1 for idiosyncratic skewness, group 20 for idiosyncratic volatility, and group 20 for price. The score for stock A equals to 1+20+20=51. We standardize this score to a value between 0 and 1: LIDX= (51-3)/60-3=0.84.

[8] For instance, the ticket prices for the two largest lotto games in the U.S., Mega Millions and Powerball, are $1 and $2, respectively. Sources: Mega Millions (http://www.megamillions.com/), Powerball (http://www.powerball.com/pb_home.asp).

3.4. Brokerage data and macroeconomic variables

To directly examine the spillover effect of jackpots on lottery-like stocks, we obtain trading data from a major U.S. discount brokerage house. This data set contains all trades of a set of individual investors during the 1991-1996 period. We examine trades on common stocks.[9] During this period, the only available multi-state lottery game is Powerball, which started from April 22, 1992. We obtain draw date, winners, and jackpot prize of each drawing from the Multi-State Lottery Association (i.e., the operator of Powerball).[10]

Additionally, we use five commonly used macroeconomic variables to account for business cycles: U.S. monthly unemployment rate (*UNEMP*), unexpected inflation (*UEI*), monthly growth in industrial production (*MP*), monthly default risk premium (*RP*), and the term spread (*TS*). We obtain *UNEMP* from the Bureau of Labor Statistics. *UEI* is the difference between the current month inflation and the average of the past 12 realizations. We obtain *MP* from the Federal Reserve. *RP* is the difference between Moody's Baa-rated and Aaa-rated corporate bond yields. *TS* is the difference between the yields of a constant maturity 10-year Treasury bond and 3-month Treasury bill. Summary statistics for these variables are reported in Panel B of Table 2.

3.5. Institutional ownership

Our second hypothesis posits that gambling sentiment would have greater impact on stocks that are more likely to be held by retail investors, i.e., small stocks or stocks with low institutional ownership. Small stocks are defined as stocks in the bottom 30th percentile by market capitalization in the CRSP universe. Firm-level institutional ownership data are collected from

[9] Details on the brokerage data are available in Barber and Odean (2000).
[10] We thank Multi-State Lottery Association for providing the historical Powerball information to us.

FactSet and based on Ferreira and Matos (2008). We measure a firm's institutional ownership in a year by its average quarterly total institutional ownership. The mean of total institutional ownership is 55% for our sample period (see Panel B of Table 2). Low institutional ownership stocks are stocks with less than ten percent total institutional ownership.

3.6. *Stock splits*

Our third economic setting focuses on the implication of time-varying gambling attitudes on stock splits. We include all common stocks in the U.S. and identify splitters as those with a CRSP distribution code of 5523. We study stock splits that reduce stock prices, so reverse stock splits are not included in our sample. Following Lin, Singh, and Yu (2009), we require splitters to have a CRSP Factor to Adjust Price (FACPR) greater than or equal to one and equal to the CRSP Factor to Adjust Shares Outstanding (FACSHR). After dropping stocks without COMPUSTAT data, our sample includes 490 stock splits from January 2005 to December 2013. The average monthly probability of stock splits is 0.12% (see Panel B of Table 2).

3.7. *IPO data*

In our fourth economic setting, we analyze the effects of time-varying gambling attitudes on first-day returns of IPOs. We obtain the monthly average first-day return on the "net IPOs" from Jay Ritter's website.[11] Net IPOs are IPOs excluding closed-end funds, REITs, acquisition companies, stocks with offer prices below $5, ADRs, limited partnerships, units, banks and S&Ls, and those not listed on CRSP, as defined in Ibbotson, Sindelar, and Ritter (1994). The first-day return is calculated as the percentage return from the offering price to the first closing

[11] See http://bear.warrington.ufl.edu/ritter/ipodata.htm.

bid price. The monthly average first-day return is calculated as the equal-weighted average of the first-day returns on all the offerings in a particular calendar month. During our sample period, the average post-IPO first-day return is 13.5% (see Panel B of Table 2).

4. Empirical results

4.1. Stock return predictability

Our first hypothesis investigates whether time-varying gambling attitudes affect stock returns. If elevated gambling sentiment increases the demand for lottery-like stocks and generates price pressure on these stocks, we expect *ASVI* to have a positive impact on the abnormal return of lottery-like stocks in the short-run. Our tests examine whether this short-term return predictability exists.

To measure the abnormal return performance of lottery-like stocks, we use the Carhart (1997) four-factor model to account for size, market-to-book, and past performance. We estimate 36-month rolling-window regressions and require all stocks to have at least 12 months of return data. After estimating the factor loadings using equation (3), we calculate the abnormal return for each stock as:

$$AR_{i,t} = r_i - r_f - \tilde{\beta}_{mkt,t-1}(r_{mkt} - r_f) - \tilde{\beta}_{smb,t-1}r_{smb} - \tilde{\beta}_{hml,t-1}r_{hml} - \tilde{\beta}_{umd,t-1}r_{umd}, \tag{4}$$

where $AR_{i,t}$ is the abnormal return of stock *i* in month *t*. Factor loadings are estimated from month *t-36* to *t-1*. The abnormal returns are then value-weighted to obtain the portfolio return.[12]

Following Da, Engelberg, and Gao (2011), we estimate the following regression to determine if stock returns are predictable in the short-run:

[12] Our results are similar if we first form portfolios and then estimate abnormal returns at the portfolio-level.

$$AR_{portfolio,t+n} = \alpha + \beta_n \times ASVI_t + \epsilon_t, \quad n = 0, 1,2, 3, \tag{5}$$

where $AR_{portfolio,t+n}$ is the average abnormal return in month $t+n$ of a stock portfolio weighted by market capitalization in month $t+n-1$. The coefficient β_n measures the predictive power of *ASVI* with n lags.

The coefficient estimates in Table 3 support our prediction. The β_n coefficients are positive in months 0 and 1 for lottery-like stock portfolio. In economic terms, a one standard deviation increase (i.e., 20%) in the *ASVI* for the topic "lottery" is associated with a significantly positive price change of 47 basis points in month 1. The coefficient estimates become negative from month two onward, indicating a subsequent price reversal as the mispricing get corrected. Economically, a one standard deviation increase in *ASVI* significantly reduces lottery-like stocks' abnormal returns in month 3 by 33 basis points. In contrast to lottery-like stock portfolio, *ASVI* does not have any power to predict the return of non-lottery stock and other stock portfolios. Further, the estimates in Column 5 show that the return predictability is stronger when we Long lottery-like stocks and Short non-lottery stocks simultaneously.

Overall, the results in Table 3 support our first hypothesis. Lottery-like stocks earn significantly positive abnormal returns when investors have stronger gambling sentiment. This is consistent with retail investors' gambling sentiment leading to short-term overpricing of lottery-like stocks.

4.2. Attention-grabbing jackpots

One potential explanation for our evidence of short-term return predictability among lottery-like stocks is that those stocks experience positive abnormal returns when investors pay more attention to lottery-related events. Hence we use lottery jackpots that grab investors' attention to identify the sources of time-variation in investors' gambling attitudes. These are exogenous events and do not require the gambling sentiment measure from Google.[13]

We define attention-grabbing jackpots in three different ways. First, the *all-time largest* jackpot of $656 million was awarded on March 30, 2012, which is the largest jackpot in the U.S. history. Second, *record-breaking* jackpots are the jackpots that break national record at the time. This criterion gives us the *all-time largest* jackpot and two other jackpots announced on February 18, 2006 and March 6, 2007. Third, we use a broader definition of *attention-grabbing* jackpots. In addition to the three *record-breaking* jackpots, we include near-record jackpots that are either the second largest jackpot at the time or the largest jackpot over the past 24 months. If two jackpots selected are next to each other such that event windows are contaminated, we drop both of them from our sample. The above criterion leads to eight attention-grabbing jackpots in our sample period.

The sizes and dates of eight attention-grabbing jackpots are reported in the Appendix (Table 1A). These jackpots take on average two months from the first to the last drawing dates. Their values are between $336 million and $656 million.

Once we identified the lottery jackpots, we use a calendar-time portfolio approach to measure the impact of attention-grabbing jackpots on stock returns:

$$r_{portfolio,t} - r_{f,t} = \alpha + \beta_1 D_{[-1,+1]}^{Jackpot} + \beta_2 D_{[+2,+3]}^{Post} + \beta_3 \left(r_{mkt} - r_f\right) + \beta_4 r_{smb} + \beta_5 r_{hml} + \beta_6 r_{umd} + \epsilon_{t,} \quad (6)$$

where the dependent variable is the average excess return of lottery-like or non-lottery stocks in month *t*. The final drawing dates of attention-grabbing jackpots are in month 0. $D_{[-1,+1]}^{Jackpot}$ is a

[13] The occurrences of large jackpots are random and are unlikely to be driven by factors that affect the stock market. For example, the winning odds for Mega Millions and Powerball jackpots in 2015 are as low as 1 in 258,890,850 and 1 in 175,223,510, respectively. Sources: websites of Mega Millions and Powerball.

dummy variable that equals to one from month -1 to month +1 and zero otherwise. β_1 measures average abnormal return during the (-1, +1) period. $D^{Post}_{[+2,+3]}$ is a dummy variable that equals to one during the (+2, +3) period and zero otherwise. β_2 measures average abnormal return during the (+2, +3) period. Standard errors are adjusted for auto-correlation using the Newey and West (1987) method.

Table 4 reports the estimated coefficients of β_1 (Panel A) and β_2 (Panel B). We find that lottery-like stocks earn significantly positive returns around attention-grabbing jackpots. The average abnormal return during the (-1, +1) period is between 1.55% and 1.75% per month. This short-term mispricing is partially corrected during the (+2, +3) period. The price reversal in months (+2, +3) is -1.23% for the all-time largest jackpot and -1.10% for the record-breaking jackpots. These results are consistent with our return predictability results in Table 3.

Next, we examine the abnormal trading volumes around jackpots. Following Chae (2005), abnormal trading volume is calculated as:

$$Abnormal\ Trading\ Volume_{i,t} = \tau_{i,t} - \bar{\tau}_i, \tag{7}$$

where $\tau_{i,t}$ is the log-transformed turnover (i.e., trading volumes divided by outstanding shares) for stock i in month t and $\bar{\tau}_i$ is the average log-transformed turnover during the estimation period, which has a length of 36 months and ends three months before the event. [14]

Table 5 presents the results. For attention-grabbing jackpots, lottery-like stocks experience significantly positive abnormal trading volume of about 17% during the (-1, +1) period and about 21% during the (+2, +3) period. This evidence suggests that changes in gambling sentiment induce changes in trading activity among lottery-like stocks.

[14] We also use an alternative approach to estimate abnormal trading volume. We adjust the log-transformed turnover by the market model where the market volume is the value-weighted log turnover of stocks listed on NYSE, AMEX and NASDAQ, as in Campbell and Wasley (1996). Results are quantitatively similar.

Overall, lottery-like stocks experience temporary overpricing and abnormal trading volume due to strong gambling sentiment among retail investors.[15] This spillover effect on lottery-like stocks is consistent with evidence from the economics literature on the betting market.[16]

4.3. Evidence from brokerage data

In this section, we directly test whether retail investors increase aggregate demand for lottery-like stocks around large jackpots. We use the data that cover trades of retail investors from a large discount brokerage house during the 1991-1996 period. We use two types of lottery measures. First, we study the largest jackpot during the 1992-1996 period (i.e., the $111 million prize announced on July 7, 1993).[17] Second, following Gao and Lin (2015) we examine large drawings, which include either claimed jackpots or unclaimed balances.

To examine the impact of the largest jackpot, we measure the aggregate demand for lottery-like stocks as the excess buy-sell imbalance (*EBSI*) defined as the difference in buy-sell imbalance between lottery-like and non-lottery stock portfolios (Kumar, 2009).[18] This measure

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[15] Gao and Lin (2015) find a negative impact of lottery jackpots (i.e. large jackpot drawings) on stock trading volume using data from Taiwan. For the U.S., Dorn, Dorn, and Sengmueller (2013) have a similar finding for the 1998-2004 period, but the effect is insignificant for the 2005-2008 period. Our paper uses a different measure of jackpots (i.e., the realization of winning jackpots) and a more recent sample in the U.S. Our result is opposite to that of Gao and Lin's (2015) study on Taiwan, which suggests that the results from Taiwan cannot be extrapolated to the U.S. setting.

[16] Related economics literature has shown that state lotteries are complements to other forms of gambling. For example, the introduction of a lottery increases the participation in casino gaming and horse racing (Scott and Garen, 1994; Calcagno, Walker, and Jackson, 2010). Increases in gambling expenditure by households are associated with reductions in non-gambling expenditure, rather than reductions in other types of gambling expenditure (Kearney, 2005). In addition, different types of U.S. lotteries complement each other (Grote and Matheson, 2007).

[17] Our sample starts from the inception of Powerball, therefore no previous jackpots that could be used to define record-breaking and attention-grabbing jackpots as in Section 4.2.

[18] The buy-sell imbalance (*BSI*) of portfolio p in month t is defined as $BSI_{pt} = \frac{100}{N_{pt}}\sum_{i=1}^{N_{pt}} BSI_{it}$, where the *BSI* for stock i in month t is defined as $BSI_{it} = \frac{\sum_{j=1}^{D_t}(VB_{ijt}-VS_{ijt})}{\sum_{j=1}^{D_t}(VB_{ijt}+VS_{ijt})}$. Here, D_t is the number of days in month t. VB_{ijt} (VS_{ijt}) is the dollar buying (selling) volume of stock i on day j in month t, and N_{pt} is the number of traded stocks in portfolio p in month t. Kumar and Lee (2006) show that an equal-weighted *BSI* measure is more appropriate for capturing shifts in investor sentiment than a value-weighted measure.

captures the change in investors' bullishness towards lottery-like stocks relative to their change in bullishness towards non-lottery stocks. Specifically, we estimate the following time-series regression:

$$EBSI_t = \alpha + \beta_1 D_{[-1,+1]}^{Jackpot} + \beta_2 MKTRET_t + \beta_3 MKTRET_{t-1} + \beta_4 LOTRET_t + \beta_5 LOTRET_{t-1}$$
$$+\beta_6 EBSI_{t-1} + Controls_{t-1} + \epsilon_t. \qquad (8)$$

The dependent variable is the monthly excess buy-sell imbalance of lottery-like stocks. Lottery-like stocks are defined as in Section 3.3. Independent variables include contemporaneous and one month lagged market returns, contemporaneous and one month lagged returns of the lottery-like stock portfolio. We also include lagged *EBSI* to control for potential serial correlation in that measure. Additionally, we include *UNEMP*, *UEI*, *MP*, *RP* and *TS* as control variables to account for business cycles since investors are known to have stronger gambling sentiment during economic recessions (Kumar, 2009). The sample period is from April 1992 to November 1996. Standard errors are calculated using the method in Newey and West (1987).

The key variable of interest is $D_{[-1,+1]}^{jackpot}$, which equals to one from month -1 to month +1 around the event jackpot, and zero otherwise. A positive and significant coefficient on $D_{[-1,+1]}^{jackpot}$ would support the spillover effect.[19] Table 6 presents the results. Consistent with our expectation, we find a significantly positive coefficient of 7% on $D_{[-1,+1]}^{jackpot}$, which suggests that the jackpot leads to 7% higher net purchase of lottery-like stocks relative to non-lottery stocks.

Next, we examine the effect of large drawings on daily *EBSI*. We have 228 large drawings during our sample period. Since Powerball drawings were held on Wednesday and Saturday

[19] Although the brokerage data cover trades of a set of retail investors from all U.S. states, only 14 states participated in Powerball at its inception in 1992. Large states such as New York and California did not join Powerball during the 1992-1996 period. Therefore, our estimation is conservative: we expect a smaller effect using brokerage data.

evenings at 10:59 pm, we examine the spillover effect on the next trading day (i.e., Thursdays and Mondays). Specifically, we estimate the following time-series regression:

$$EBSI_t = \alpha + \beta_1 D_t^{Drawing} + \beta_2 MKTRET_t + \beta_3 LOTRET_t + \beta_4 EBSI_{t-1} + \beta_5 VIX_{t-1} + \beta_6 ADS_{t-1} + Controls + \epsilon_t. \tag{9}$$

The dependent variable is daily excess buy-sell imbalance of lottery-like stocks. Independent variables include market return, return of the lottery-like stock portfolio, and lagged *EBSI*. We also include the lagged Chicago Board Options Exchange daily market volatility index (*VIX*) to account for investor fear and market sentiment, and include lagged Aruoba-Diebold-Scotti business conditions index (*ADS*) to account for daily economic condition (Da Engelberg, and Gao, 2015). Control variables include lagged market and lottery-like stock portfolio returns (up to five lags) and day-of-the-week dummies. Standard errors are calculated using the method in Newey and West (1987).

The key variable of interest is $D_t^{Drawing}$, which equals to one on the next trading day following a large drawing, and zero on days with no drawings or small drawings. A large (small) drawing has above (below) median drawing value during the April 22, 1992 to November 30, 1996 period. Table 7 presents the results. We find a significantly positive coefficient of 3% on $D_t^{Drawing}$, which suggests that large drawings lead to 3% more net purchase of lottery-like stocks relative to non-lottery stocks. The magnitude of *EBSI* is smaller because large drawings attract less attention than claimed jackpots.

Overall, Tables 6 and 7 show that attention-gabbing jackpots would motivate retail investors to increase their demand for lottery-like stocks. This suggests that shifts in gambling attitudes have a spillover effect on the stock market.

4.4. Cross-sectional variation

In this section, we study whether cross-sectional differences in gambling sentiment shifts affect stock performance in the long-term. We use the average state-level *SVI* for the topic “lottery” to form portfolios based on gambling sentiment of the state in which a firm is headquartered. Value-weighted portfolios are constructed for lottery-like, non-lottery, and other stocks. Abnormal returns are estimated as alpha from monthly return regressions with the Carhart (1997) four factors as the benchmark.

Table 8 shows that lottery-like stocks significantly underperform non-lottery stocks. A portfolio strategy that goes long in lottery-like stocks and goes short in non-lottery stocks significantly underperform the Carhart (1997) benchmark by 43 basis points per month. The effect is driven by firms headquartered in states with strong gambling sentiment. In contrast, lottery-like and non-lottery stocks do not have significantly different performance when they are headquartered in states with either moderate or weak gambling sentiment.

Next, we study cross-sectional differences among firms that are headquartered in states with strong gambling sentiment. Table 9 reports the long-term performance of stocks sorted by institutional ownership or firm size. Panel A shows that lottery-like stocks have larger underperformance when the institutional ownership is lower. Specifically, lottery-like stocks underperform non-lottery stocks by about 1.3% per month for stocks with below ten percent institutional ownership. The abnormal return difference reduces to 53 basis points for stocks with above ten percent institutional ownership.

Panel B shows that for stocks ranked in the bottom 30% by size, lottery-like stocks significantly underperform non-lottery stocks by 1.4% per month. In contrast, such underperformance does not exist for large stocks. These findings suggest that gambling sentiment has a larger impact on stocks returns for stocks that are more likely to be held by retail investors.

Collectively, the results in Tables 8 and 9 support our second hypothesis. Consistent with our conjecture, in regions with strong gambling sentiment, local investors are willing to accept a negative risk-adjusted return for lottery-like stocks. This results is more pronounced for stocks with low institutional ownership or small market capitalization. In contrast, in regions with weak gambling sentiment, lottery-like stocks do not underperform non-lottery stocks.

4.5. Stock splits

Our third hypothesis posits that an increase in gambling sentiment would lead to a higher probability of stock splits for stocks with high nominal prices. Previous literature has shown that firms are more likely to split their shares when stock prices are high (e.g., Baker and Powell, 1992; Dyl and Elliott, 2006; Minnick and Raman, 2014). We use logistic regression to estimate the influence of gambling sentiment on stock splits. The dependent variable in this regression is equal to one if the company splits its shares in a given month, and zero otherwise. We control for stock return, lagged firm size, and market-to-book ratio. We also control for split activities in the previous year. Specifically, we run the following logistic regression:

$$Logit(Split_{i,t}) = \alpha + \beta_1 D_{ASVI_{t-1}} + \beta_2 D_{p_{i,t-1}} + \beta_3 D_{ASVI_{t-1}} \times D_{p_{i,t-1}} + \beta_4 return_{i,t} +$$

$$\beta_5 size_{i,t-1} + \beta_6 MTB_{i,t-1} + \beta_7 splitter_{i,t-12} + \epsilon_{t,} \tag{10}$$

where $D_{ASVIt-1}$ is a dummy variable that equals one if investors have strong gambling sentiment. We define strong gambling sentiment as *ASVI* values above the 75th percentile value of the time-series. $Dp_{i,t-1}$ is a dummy variable of price that equals to one if a given stock is a high-priced stock. A high-priced stock has share prices above the 75th price percentile of all common stocks in the CRSP universe in a given month.[20] $D_{ASVIt-1} \times Dp_{i,t-1}$ is the interaction between the price and the gambling sentiment dummy variables.

Among other variables, $return_{i,t}$ is the return excluding dividends of stock i over the course of the month t, as in Baker, Greenwood, and Wurgler (2009). $Size_{i,t-1}$ is the natural logarithm of the market capitalization of stock i in month t-1 while $MTB_{i,t-1}$ is the market-to-book ratio defined as the market value of the firm over its book value. Market value equals to market equity at calendar year-end plus book debt, while book value is calculated as stockholders' equity minus preferred stock plus deferred taxes and investment tax credits and post retirement assets. $Splitter_{i,t-12}$ is a dummy variable that equals to one if a firm split its stocks in the previous year. Standard errors are clustered by firm and by date.

The key variable of interest is the interaction between the price and gambling sentiment dummy variables. We expect that the splitting propensity would be high when share price is high and gambling sentiment is strong.

Table 10 reports the estimation results. We find that the interaction term between price and gambling sentiment dummy variables is positively significant in all specifications, which supports our third hypothesis. The gambling sentiment dummy variable is insignificant while the price dummy variable is significant at the 1% level. This evidence suggests that gambling sentiment affects the split probability only when share price is high. In economic terms, a one unit increase in the dummy variable for gambling sentiment raises the split probability by 0.10%

[20] During our sample period, the average value of the 75th price percentiles is $30 with a minimum value of $15 and a maximum of $43. Our definition of high-priced stock is similar to the 70th price percentile used in Baker, Greenwood, and Wurgler (2009). Our definition of high-priced stocks is also motivated by the minimum bid price requirements of major stock exchanges. Both NYSE and NASDAQ require listed firms to have a share price of at least $1. Firms that fail to meet this requirement can be delisted. During the 2007 financial crisis, hundreds of firms traded below $2. In 2008 alone, 85 firms (10% of all listed firms in NASDAQ) were delisted from NASDAQ, mostly for not meeting the $1 price requirement. In general, firms trading in the sub-$5 range face substantial delisting risk.

per month.[21] This effect is economically significant since the average monthly split probability is 0.12%. In addition, we find that small stocks and stocks with higher returns are more likely to split, which is consistent with the existing literature.

Overall, the evidence in Table 10 provides support to our third hypothesis. We demonstrate that retail investors' gambling sentiment plays an important role in explaining the time-varying demand for low-priced stocks. When investors' gambling sentiment is strong, high-priced firms are more likely to split stocks to cater to the excess demand for low-priced stocks.

4.6. Underpricing of IPOs

In this section, we focus on our fourth hypothesis and examine whether gambling sentiment helps to explain the time-variation in IPOs' first-day returns. We regress the average monthly first-day return of the net IPOs against lagged *ASVI*. Following Baker, Greenwood, and Wurgler (2009), we control for the average log price at the beginning of the month and the value-weighted market return excluding dividends over the course of the month. We also include the hotness of IPO market and the monthly number of net IPOs as additional controls. Our sample period for the test is from January 2005 to June 2014. This gives us a time-series of 107 monthly observations with IPO data.

We estimate the following regression:

$$r_t^{IPO} = \alpha + \beta_1 ASVI_{t-1} + \beta_2 p_{t-1} + \beta_3 VWMKT_t + \beta_4 hotness_t + \beta_5 IPOnumber_t + \epsilon_{t,} \tag{11}$$

[21] In specification 5, when the price dummy variable equals to one and the *ASVI* dummy variable equals to zero, the predicted split probability is 0.51% per month keeping control variables at their mean. In contrast, the predicted split probability increases to 0.61% if the *ASVI* dummy variable increases to one.

where p_{t-1} is the equally-weighted average log price in the previous month by using all common stocks in the CRSP universe, and $VWMKT_t$ is the value-weighted return of all common stocks over the course of month *t*. Following Ibbotson, Sindelar, and Ritter (1994), $Hotness_t$ is the percentage of deals that priced above the midpoint of the original file price range in month *t*. $IPO\ number_t$ is the natural logarithm of the monthly number of net IPOs in month *t*.

Table 11 reports the estimation results. After controlling for the market return, average price level and the hotness of IPO market, the coefficients of *ASVI* are positive and significant at the 1% level. Economically, a one standard deviation increase in *ASVI* (i.e., 20%) is associated with a 1.62% increase in the average first-day IPO return. Relative to the mean first-day return of 13.44%, this reflects an economically meaningful 12.05% increase. Consistent with our fourth hypothesis, this evidence suggests that when investors have stronger gambling sentiment, IPOs experience a higher average first-day return.

4.7. Robustness checks and alternative explanations

In this section, we conduct a number of robustness checks for our baseline results. First, we include five commonly used macroeconomic variables in our return predictability regressions to account for business cycles since investors are more likely to gamble during economic recessions (Kumar, 2009). The estimation results are reported in Panel A of Table 12, which are similar to the return predictability estimates in Table 3. We find that business cycles in the U.S. do not explain the predictive power of our gambling sentiment measure.

Second, we test if our findings can be explained by other investor sentiment proxies. For example, Baker and Wurgler (2006, 2007) construct an investor sentiment index by using the first principal component of six sentiment proxies, where each of the proxies has been orthogonalized with respect to a set of macroeconomic conditions. The data are available until

2010. In Panel B of Table 12, Column 1 (2) reports the return predictability results without (with) the investor sentiment variable from Baker and Wurgler (2007). Our results remain similar, which suggests that our results on gambling sentiment cannot be explained by the other general investor sentiment measures.

Third, search volume intensity from Google was publicly available only after June 2006. Column 3 shows that our return predictability results are similar for the sub-period that starts in June 2006. In Column 4, we also control for the market-wide investor sentiment for this sub-period and our results remain similar. Thus, the predictive pattern in stock returns that we document exists even after Google's search volume intensity data are publicly available.

Fourth, we conduct several robustness checks for our stock split analysis. These results are summarized in Panel C of Table 12. In Column 1, we include firm fixed effects to control for unobservable firm characteristics. This allows us to focus on firms that have time-series variations in stock splits. Our results remain similar. In addition, in Columns 2 to 7, we include macroeconomic controls and our results still hold. In untabulated tests, we also include returns over the past three, six, or twelve months as additional control variables, since past literature suggests that split decisions are a function of a long period of lagged returns. Our results remain similar after including these lagged returns.

In the last robustness check, we reconsider the first-day IPO returns analysis, where we include five macroeconomic variables in the regression specification. Our results remain robust (see Panel D of Table 12).

5. Conclusion

This study investigates how changes in overall attitudes toward gambling affect financial market outcomes. Using a novel measure of gambling sentiment based on lottery-related Internet search volume, we show that the time-variation in gambling attitudes predicts the returns of lottery-like stocks. By using attention-grabbing lottery jackpots as our natural experiments, we further show that these results are not explained by reverse causality. Large lottery jackpots not only increase people's participation in lotteries, but also enhance investors' propensity to purchase stocks with lottery-like characteristics. By analyzing trades of retail investors from a major U.S. discount brokerage firm, we show that investors increase aggregate demand for lottery-like stocks around the largest jackpot or following large drawings.

Examining geographical differences, we find that in U.S. states where gambling attitudes are strong, lottery-like stocks underperform stocks that are otherwise similar in the long-run. These effects are stronger for stocks with lower institutional ownership or smaller size.

The time-variation in gambling attitudes also affects corporate financial decisions. Specifically, firms with high nominal share prices are more likely to split their shares when investors’ gambling sentiment becomes stronger. Stronger gambling sentiment is also associated with higher first-day returns of initial public offerings. Collectively, these results suggest that shifts in overall gambling attitudes have a spillover effect on the stock market.

These findings contribute to the growing finance literature that examines the role of gambling in financial markets. Our paper adds a new dimension to this literature by demonstrating that time-variation in gambling attitudes generates short-term mispricing and also affects corporate decisions. In future work, it may be interesting to examine whether time-varying gambling attitudes influence mutual fund flows. Mutual funds that hold more lottery-like stocks could experience more cash inflows when gambling sentiment is strong. It would also be interesting to examine the influence of time-varying gambling sentiment on other lottery-like securities such as options.

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Table 1
Top and bottom states in gambling sentiment

This table reports characteristics of the top and bottom five states in terms of the average search volume intensity for the topic "Lottery" from 2004 to 2013. *Annual sales* (reported in million $) presents the total lottery sales value in fiscal year 2012. *Population* shows the state-level total population according to the 2010 Census. *Per capital sales* is calculated as lottery sales divided by population. *Education* reports the proportion of state population over the age of 25 that has obtained a bachelor's degree or higher. *Launch year* reports the year when the first state lottery ticket is on sale. *Average SVI* is the average annual search volume intensity, which is aggregated from weekly SVIs.

Panel A: Top five states in gambling sentiment

States	(1) *Annual sales*	(2) *Population*	(3) *Per capital sales*	(4) *Education*	(5) *Launch year*	(6) *Average SVI*
Florida	4,449.90	18,801,310	236.68	26.52	1988	147.34
Georgia	3,834.70	9,687,653	395.83	29.52	1993	92.23
Massachusetts	4,741.40	6,547,629	724.14	39.05	1972	77.04
Michigan	2,413.46	9,883,640	244.19	26.31	1972	75.42
Tennessee	1,311.00	6,346,105	206.58	23.42	2004	73.14
Average	3,350.09	10,253,267	361.48	28.96		93.03
Median	3,834.70	9,687,653	244.19	26.52		77.04

Panel B: Bottom five states in gambling sentiment

States	(1) *Annual sales*	(2) *Population*	(3) *Per capital sales*	(4) *Education*	(5) *Launch year*	(6) *Average SVI*
Hawaii	N/A	1,360,301	N/A	29.52	N/A	9.96
Utah	N/A	2,763,885	N/A	30.29	N/A	10.15
Alaska	N/A	710,231	N/A	26.67	N/A	11.37
Idaho	175.84	1,567,582	112.17	25.70	1989	12.04
Vermont	100.93	625,741	161.30	34.82	1978	13.69
Average	138.39	1,405,548	136.73	29.40		11.44
Median	138.39	1,360,301	136.73	29.52		11.37

Table 2
Summary statistics

This panel reports the characteristics for lottery-like stocks, non-lottery stocks, and other stocks. Variables are calculated as the monthly average from 2005 to 2013. Lottery-like stocks are defined as stocks within the upper 30 percentiles of Lottery Index (LIDX) in each year. Similarly, Non-lottery stocks are defined as stocks in the bottom 30 percentiles of LIDX in each year. Other stocks are defines as the rest of stocks in CRSP. *Number of stocks* reports the average number of lottery-like, non-lottery, other and all common stocks in the CRSP universe in each year. *Stock price* is the average price. *Stock return* is the monthly realized return. *Firm size* in million U.S. dollar is calculated as stock price multiplied by shares outstanding. *MTB Ratio* is defined as the market value of the firm over its book value. Market value equals to market equity at calendar year-end plus book debt while book value is calculated as stockholders' equity minus preferred stock plus deferred taxes and investment tax credits and post retirement assets. *Trading volume* is the log-transformed turnover (i.e., total shares traded divided by outstanding shares). *Idiosyncratic volatility* is the standard deviation of the residual from Carhart (1997) model. *Total skewness* (*kurtosis*) is the third (fourth) moment of monthly stock returns. *Idiosyncratic skewness* is the scaled measure of the third moment of the residual from a two factor model (i.e., equation (2)). *Observations* is the number of firm-month observations.

Panel A: Characteristics of lottery-like stocks

Variables	(1) Lottery-like stocks	(2) Non-lottery stocks	(3) Other stocks	(4) CRSP all stocks
Number of stocks	1,269	1,288	1,721	4,278
Stock price	5.67	135.03	19.42	51.10
Stock return	0.87%	0.80%	0.84%	0.84%
Firm size ($M)	266.54	8,995.79	1,694.37	3,534.46
Total volatility	19.63%	8.61%	12.40%	13.39%
Idiosyncratic volatility	18.80%	7.62%	11.40%	12.48%
Total skewness	0.52	0.08	0.23	0.27
Idiosyncratic skewness	0.54	0.15	0.28	0.32
Kurtosis	1.19	0.51	0.67	0.77
MTB ratio	2.22	1.68	1.73	1.85
Trading Volume	-2.71	-2.14	-2.37	-2.40
Observations	127,858	137,200	180,136	445,194

Table 2 (Cont'd)

This panel reports the summary statistics of other variables for our empirical analyses. *IPO return* is the monthly average first-day return (in percentage) on the net IPOs. *Hotness* reports the percentage of deals that priced above the midpoint of the original file price range. *IPO number* is the natural logarithm of the monthly number of net IPOs. All the above three variables are obtained from Jay Ritter's website. *Market return* (i.e., $VWMKT_t$ in equation (11)) reports the value-weighted monthly percentage return excluding dividends for all stocks in the CRSP universe. *UNEMP* reports the U.S. monthly unemployment rate obtained from the Bureau of Labor Statistics. *UEI* is the unexpected inflation (i.e., current month inflation minus the average of the past 12 realizations). *MP* is the monthly growth in industrial production obtained from the Federal Reserve. *RP* is the monthly default premium (i.e., difference between Moody's Baa-rated and Aaa-rated corporate bond yields) obtained from the Federal Reserve Bank of St. Louis. *TS* is the term spread (i.e., difference between the yields of a constant maturity 10-year Treasury bond and 3-month Treasury bill). *Split* is the monthly average splitting probability in percentage. *IO* is the annual total institutional ownership. *Stock* r*eturn* (i.e., $return_{i,\ t}$ in equation (10)) reports the stock-level monthly percentage return excluding dividends. *Ln (Size)* is the natural logarithm of market capitalization. *Std dev* reports the standard deviation. We also report the 25, 50, and 75 percentiles. N reports the number of observations. The sample period is from 2005 to 2013 for most variables.

Panel B: Other variables

Variables	(1) Mean	(2) Std dev	(3) 25th Pctl	(4) 50th Pctl	(5) 75th Pctl	(6) N
IPO return	13.44	9.68	8.40	12.50	18.00	107
Hotness	37.79	23.31	22.00	40.00	50.00	107
IPO number	2.21	0.68	1.61	2.40	2.71	107
Market return	0.85	3.80	-1.47	1.15	3.40	107
UNEMP	7.04	1.98	5.00	7.40	9.00	108
UEI	-0.01	0.47	-0.24	0.01	0.29	108
MP	0.07	0.81	-0.20	0.20	0.55	108
RP	1.19	0.55	0.90	0.98	1.29	108
TS	1.82	1.21	0.77	1.97	2.78	108
Split	0.12	0.14	0.03	0.07	0.19	108
IO	55.14	32.61	25.41	58.93	85.40	33,095
Stock return	0.54	16.40	-6.66	0.00	6.60	373,847
Ln (Size)	12.91	2.01	11.45	12.81	14.24	373,847

Table 3
Stock return predictability

This table reports the predictive power of our Google gambling sentiment measure. We regress portfolio abnormal returns on the abnormal search volume intensity for the topic "Lottery":

$$AR_{portfolio,\, t+n} = \alpha + \beta_n \times ASVI_t + \varepsilon_t, (n=0, 1, 2, 3).$$

ASVI is the abnormal search volume intensity based on the time-series difference in log search volume intensities (see equation (1)). We estimate the abnormal return of individual stocks by 36 months rolling window regressions. We use the Carhart (1997) four-factor model as benchmark. We then form value-weighted portfolios of lottery-like, non-lottery, and other stocks. Lottery-like stocks are defined as stocks within the upper 30 percentiles of Lottery Index (LIDX) in each year. Non-lottery stocks are defined as stocks in the bottom 30 percentiles of LIDX in each year. Other stocks are the rest of stocks in the CRSP universe. β_n measure the predictive power of *ASVI* with n lags. Column (1) indicates the *month n* (n=0, 1, 2, 3). Columns (2) to (4) report the regression coefficients on *ASVI* (β_n) for lottery-like, non-lottery, and other stock portfolios, respectively. Firms in the three portfolios are rebalanced in every January while portfolio weights are adjusted in every month according to market capitalization in the previous month. Column 5 reports the coefficient estimates of a portfolio strategy that goes long in lottery-like stocks and goes short in non-lottery stocks. The sample period is from January 2005 to December 2013. *N months* reports the number of months. Standard errors (reported in parentheses) are adjusted for auto-correlation using the Newey and West (1987) method. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

(1) Months	(2) Lottery-like stocks	(3) Non-lottery stocks	(4) Other stocks	(5) Long-short portfolio
0	**0.847**	**-0.140**	**0.416**	**0.987**
	(0.925)	(0.145)	(0.453)	(0.961)
1	**2.339****	**-0.025**	**-0.586**	**2.365****
	(0.947)	(0.137)	(0.509)	(1.000)
2	**-1.372**	**-0.003**	**0.308**	**-1.369**
	(0.976)	(0.199)	(0.360)	(1.021)
3	**-1.653****	**0.199**	**-0.522***	**-1.852****
	(0.787)	(0.136)	(0.307)	(0.827)
N months	108	108	108	108

Table 4
Stock performance around attention-grabbing jackpots

This table reports the average abnormal return for lottery-like and non-lottery stocks around attention-grabbing jackpots. We define attention-grabbing jackpots in three different ways. First, the *all-time largest* jackpot is the $656 million jackpot announced on March 30, 2012, which is the largest jackpot in the U.S. history. Second, *record-breaking* jackpots are the jackpots that break national record at the time. They include the all-time largest jackpot and two other jackpots announced on February 18, 2006 and March 6, 2007. Third, we use a broader definition of *attention-grabbing* jackpots. In addition to the above three record-breaking jackpots, we include five near-record jackpots that are either the second largest jackpot at the time or the largest jackpot over the past 24 months. We estimate the following regression:

$$r_{portfolio,t} - r_{f,t} = \alpha + \beta_1 D_{[-1,+1]}^{Jackpot} + \beta_2 D_{[+2,+3]}^{Post} + \beta_3\left(r_{mkt} - r_f\right) + \beta_4 r_{smb} + \beta_5 r_{hml} + \beta_6 r_{umd} + \epsilon_{t,}.$$

Dependent variable is the average excess return of lottery-like or non-lottery stocks in month *t*. The final drawing dates of attention-grabbing jackpots are in month 0. $D_{[-1,+1]}^{Jackpot}$ is a dummy variable that equals to one from month -1 to month 1 and zero otherwise. β_1 measures average monthly abnormal return for the (-1, +1) period. $D_{[+2,+3]}^{Post}$ is a dummy variable that equals to one for the (+2, +3) period and zero otherwise. β_2 measures average monthly abnormal return for the (+2, +3) period. Panel A (B) reports the estimated coefficients of β_1 (β_2). *Long-short portfolio* is a portfolio strategy that goes long in the lottery-like stock portfolio and goes short in the non-lottery stock portfolio. The sample period is from January 2005 to December 2013. Standard errors (reported in parentheses) are adjusted for auto-correlation using the Newey and West (1987) method. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Average monthly abnormal return during months (-1, +1)

Jackpot type	Lottery-like stocks	Non-lottery stocks	Long-short portfolio
All-time largest	**1.750*** **	**0.047**	**1.704*** **
	(0.416)	(0.189)	(0.519)
Record-breaking	**1.546** **	**-0.137**	**1.683*** **
	(0.597)	(0.122)	(0.605)
Attention-grabbing	**1.694* **	**-0.164**	**1.858* **
	(0.865)	(0.139)	(0.941)

Panel B: Average monthly abnormal return during months (+2, +3)

Jackpot type	Lottery-like stocks	Non-lottery stocks	Long-short portfolio
All-time largest	**-1.225* **	**-0.090**	**-1.135* **
	(0.678)	(0.106)	(0.638)
Record-breaking	**-1.100* **	**0.114**	**-1.214** **
	(0.610)	(0.199)	(0.578)
Attention-grabbing	**-0.395**	**0.236**	**-0.630**
	(0.752)	(0.147)	(0.805)

Table 5
Trading volume around attention-grabbing jackpots

This table reports the abnormal trading volume of lottery-like and non-lottery stocks around attention-grabbing jackpots. We define attention-grabbing jackpots in three different ways. First, the *all-time largest* jackpot is the $656 million jackpot announced on March 30, 2012, which is the largest jackpot in the U.S. history. Second, *record-breaking* jackpots are the jackpots that break national record at the time. They include the all-time largest jackpot and two other jackpots announced on February 18, 2006 and March 6, 2007. Third, we use a broader definition of *attention-grabbing* jackpots. In addition to the above three record-breaking jackpots, we include five near-record jackpots that are either the second largest jackpot at the time or the largest jackpot over the past 24 months. Abnormal trading volume is estimated as the difference between log-transformed turnover (the total number of shares traded divided by shares outstanding) in month *t* and the average log-transformed turnover in the estimation period. The estimation period has a length of 36 months and ends three months before the event month. Panel A reports the average abnormal trading volume in months (-1, +1) for the all-time largest, recording-breaking, and attention-grabbing jackpots. Panel B reports the average abnormal trading volume in months (+2, +3). The sample period is from January 2005 to December 2013. Standard errors (reported in parentheses) are clustered by events and by firms. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Average abnormal trading volume during months (-1, +1)

Jackpot type	Lottery-like stocks	Non-lottery stocks	Difference
All-time largest	**1.556**	**-15.338*** **	**16.893*** **
	(1.604)	(0.668)	(1.738)
Record-breaking	**14.040** **	**7.046**	**6.994**
	(6.807)	(10.039)	(15.709)
Attention-grabbing	**17.170*** **	**-4.602**	**21.772** **
	(5.987)	(6.079)	(8.532)

Panel B: Average abnormal trading volume during months (+2, +3)

Jackpot type	Lottery-like stocks	Non-lottery stocks	Difference
All-time largest	**1.536**	**-1.765***	**3.301**
	(2.166)	(0.934)	(2.359)
Record-breaking	**18.086** **	**19.186***	**-1.100**
	(7.909)	(10.694)	(26.367)
Attention-grabbing	**20.975*** **	**-0.244**	**21.219** **
	(5.930)	(7.927)	(9.900)

Table 6

Aggregate demand for lottery-like stocks: the largest jackpot during 1992-1996 period

This table reports the excess buy-sell imbalance (*EBSI*) of lottery-like stocks around the largest Powerball jackpot announced on July 7, 1993. We run the following time-series regression:

$$EBSI_t = \alpha + \beta_1 D_{[-1,+1]}^{Jackpot} + \beta_2 MKTRET_t + \beta_3 MKTRET_{t-1} + \beta_4 LOTRET_t + \beta_5 LOTRET_{t-1} + \beta_6 EBSI_{t-1} + Controls + \epsilon_t.$$

$EBSI_t$ is the month *t* difference in buy-sell imbalance between lottery-like and non-lottery stocks. $D_{[-1,+1]}^{Jackpot}$ is a dummy variable that equals one from month -1 to month 1 around the largest jackpot, and zero otherwise. Other independent variables include contemporaneous and one month lagged market returns ($MKTRET_t$, $MKTRET_{t-1}$), contemporaneous and one month lagged returns of the lottery-like stock portfolio ($LOTRET_t$, $LOTRET_{t-1}$), and *EBSI* in the previous month. Control variables include five macroeconomic variables: U.S. monthly unemployment rate (*UNEMP*), unexpected inflation (*UEI*), monthly growth in industrial production (*MP*), monthly default risk premium (*RP*), and the term spread (*TS*). The sample period is from April 1992 to November 1996. *N months* reports the number of months. Standard errors (reported in parentheses) are adjusted for auto-correlation using the Newey and West (1987) method. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
$D_{Jackpot}$	**9.476*****	**9.253*****	**10.473*****	**9.343****	**7.059***
	(3.159)	(3.183)	(3.887)	(4.135)	(4.045)
$MKTRET_t$	**0.863****	**0.845****	**-1.177**	**-0.922**	**-1.107**
	(0.410)	(0.388)	(1.264)	(1.349)	(1.234)
$MKTRET_{t-1}$		**0.144**	**-0.261**	**-1.182**	**-1.526**
		(0.430)	(0.450)	(1.215)	(1.278)
$LOTRET_t$			**1.417**	**1.307**	**1.549***
			(0.871)	(0.911)	(0.845)
$LOTRET_{t-1}$				**0.667**	**0.720**
				(0.716)	(0.777)
$EBSI_{t-1}$					**0.257****
					(0.115)
Constant	**30.370****	**31.153****	**32.223****	**33.576****	**27.603***
	(13.657)	(14.122)	(15.171)	(16.221)	(14.766)
Controls	Yes	Yes	Yes	Yes	Yes
N months	56	56	56	56	56
Adjusted R^2	0.167	0.152	0.201	0.200	0.227

Table 7
Aggregate demand for lottery-like stocks: large drawings

This table reports the daily buy-sell imbalance (*EBSI*) of lottery-like stocks following large Powerball drawings. We run the following time-series regression:

$$EBSI_t = \alpha + \beta_1 D_t^{Drawing} + \beta_2 MKTRET_t + \beta_3 LOTRET_t + \beta_4 EBSI_{t-1} + \beta_5 VIX_{t-1} + \beta_6 ADS_{t-1} + Controls + \epsilon_t.$$

$EBSI_t$ is the day t difference in buy-sell imbalance between lottery-like and non-lottery stocks. $D_t^{Drawing}$ is a dummy variable that equals to one on the next trading day following a large drawing, and zero on days with no drawings or small drawings. A large (small) drawing has above (below) median drawing value during the sample period. Other independent variables include market return, return of the lottery-like stock portfolio, and lagged *EBSI*. VIX_{t-1} is the lagged Chicago Board Options Exchange (CBOE) daily market volatility index. ADS_{t-1} is the lagged Aruoba-Diebold-Scotti business conditions index. Control variables include lagged market and lottery-like stock portfolio returns (up to five lags) and day-of-the-week dummies. The sample period is from April 22, 1992 to November 30, 1996. *N days* reports the number of trading days. Standard errors (reported in parentheses) are adjusted for auto-correlation using the Newey and West (1987) method. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
$D_{Drawing}$	**3.423***	**3.293***	**3.178***	**3.170***	**3.080***
	(1.785)	(1.783)	(1.716)	(1.721)	(1.693)
$MKTRET_t$	**3.114*****	**6.856****	**6.047****	**6.061****	**5.673****
	(1.189)	(2.740)	(2.800)	(2.804)	(2.769)
$LOTRET_t$		**-3.273**	**-2.769**	**-2.780**	**-2.570**
		(2.064)	(2.131)	(2.140)	(2.119)
$EBSI_{t-1}$			**0.179*****	**0.179*****	**0.157*****
			(0.040)	(0.040)	(0.040)
VIX_{t-1}				**-0.054**	**0.287**
				(0.383)	(0.410)
ADS_{t-1}					**-6.737*****
					(1.719)
Constant	**2.260***	**2.519***	**1.963**	**2.744**	**-0.800**
	(1.316)	(1.338)	(1.287)	(5.793)	(5.976)
Controls	Yes	Yes	Yes	Yes	Yes
N days	1,167	1,167	1,167	1,167	1,167
Adjusted R^2	0.021	0.022	0.053	0.052	0.068

Table 8
Stock performance of U.S. states sorted by gambling sentiment

This table reports the performance of a value-weighted portfolio of lottery-like or non-lottery stocks. Abnormal return is measured as the intercept of monthly return regressions by using the Carhart (1997) four factor model as benchmark. *Full sample* reports the abnormal portfolio returns for all stocks in our sample. *Strong (moderate) (weak) sentiment* reports the abnormal portfolio returns of stocks headquartered in U.S. states with strong (moderate) (weak) gambling sentiment. *Strong-weak* (*strong-moderate*) measures the abnormal return difference between stocks located in states with strong and weak (moderate) gambling sentiment. Strong (moderate) (weak) gambling sentiment state group includes 17 states with top (medium) (bottom) average search volume intensity for the topic "Lottery". The three groups of states are updated in January of each year. *Long-short portfolio* is a portfolio strategy that goes long in the lottery-like stock portfolio and goes short in the non-lottery stock portfolio. The sample period is from January 2005 to December 2013. *N months* reports the number of months. Standard errors (reported in parentheses) are adjusted for auto-correlation using the Newey and West (1987) method. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) Lottery-like stocks	(2) Non-lottery stocks	(3) Long-short portfolio
Full sample	**-0.422***	**0.010**	**-0.432***
	(0.222)	(0.033)	(0.242)
Strong sentiment	**-0.542****	**0.060**	**-0.602****
	(0.225)	(0.054)	(0.253)
Moderate sentiment	**-0.143**	**-0.045**	**-0.098**
	(0.284)	(0.080)	(0.285)
Weak sentiment	**0.146**	**-0.056**	**0.202**
	(0.447)	(0.151)	(0.477)
Strong – weak	**-0.687***	**0.116**	**-0.803***
	(0.394)	(0.159)	(0.427)
Strong – moderate	**-0.399**	**0.105**	**-0.504****
	(0.251)	(0.113)	(0.240)
N months	108	108	108

Table 9

Performance of stocks headquartered in U.S. states with strong gambling sentiment

This table reports the performance of a value-weighted portfolio of stocks located in U.S. states with strong gambling sentiment. Abnormal return is measured as the intercept is of monthly return regressions by using the Carhart (1997) four-factor model as benchmark. Panel A reports the long-term performance of stocks with different levels of institutional ownership (*IO*). *Low (high) IO* is the abnormal return of a value-weighted portfolio of lottery-like or non-lottery stocks with less (more) than ten percent institutional ownership. Panel B reports the long-term performance of stocks with different market capitalizations. *Small (large)* is the abnormal return of stocks in the bottom (top) 30% by size. *Low- high (Small- large)* reports the abnormal return difference between the same types of stocks with different levels of institutional ownership (market capitalizations). *Long-short portfolio* reports the abnormal return earned by a portfolio strategy that goes long in lottery-like stocks and goes short in non-lottery stocks. The sample period is from January 2005 to December 2013. *N months* reports the number of months. Standard errors (reported in parentheses) are adjusted for auto-correlation using the Newey and West (1987) method. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Stocks sorted by institutional ownership

	(1) Lottery-like stocks	(2) Non-lottery stocks	(3) Long-short portfolio
Low IO	**-1.237*****	**0.112**	**-1.349*****
	(0.334)	(0.405)	(0.503)
High IO	**-0.465****	**0.064**	**-0.529****
	(0.223)	(0.056)	(0.250)
Low – high	**-0.772****	**0.048**	**-0.821***
	(0.331)	(0.406)	(0.455)
N months	108	108	108

Panel B: Stocks sorted by firm size

	(1) Lottery-like stocks	(2) Non-lottery stocks	(3) Long-short portfolio
Small	**-3.427*****	**-1.989*****	**-1.438*****
	(0.384)	(0.443)	(0.390)
Large	**-0.050**	**0.062**	**-0.111**
	(0.248)	(0.054)	(0.272)
Small - large	**-3.377*****	**-2.050*****	**-1.327*****
	(0.451)	(0.456)	(0.422)
N months	108	108	108

Table 10
Gambling sentiment and stock splits

This table reports the results of our logistic estimate. We run the following regressions:

$$Logit\ (Split_{i,t}) = \alpha + \beta_1 D_{ASVIt-1} + \beta_2\ Dp_{i,t-1} + \beta_3 D_{ASVIt-1} \times Dp_{i,t-1} + \beta_4 Return_{i,t} + \beta_5 Size_{i,t-1} + \beta_6 MTB_{i,t-1} + \beta_7 Spllitter_{i,t-12} + \varepsilon_{t.}.$$

Dependent variable is equal to one if a company splits its shares in a given month. Independent variables include a dummy variable of the abnormal search volume intensity for the topic" Lottery" ($D_{ASVIt-1}$), a dummy variable of stock prices ($Dp_{i,t-1}$), and their interaction term ($D_{ASVIt-1} \times Dp_{i,t-1}$). We use 75th percentile as the break points for both dummies. $D_{ASVIt-1}$ is equal to one if it has a value above the 75th percentile of the time-series. Similarly, D_{pt-1} is equal to one if a firms' price is above the 75th percentile of all stock in the CRSP universe in a given month. Control variables include size ($Size_{i,t-1}$) and market-to-book ratio ($MTB_{i,t-1}$) at the beginning of the month and return ($Return_{i,t}$) over the course of the month. $Size_{i,t-1}$ is the natural logarithm of the market capitalization of stock *i* in month *t-1* while $MTB_{i,t-1}$ is defined as the market value of the firm over its book value. Market value equals to market equity at calendar year-end plus book debt while book value is calculated as stockholders' equity minus preferred stock plus deferred taxes and investment tax credits and post retirement assets. $Splitter_{i,t-12}$ is equal to one if a firm splits its share in the previous year. The sample period is from January 2005 to December 2013. *Observations* is the number of firm-month observations. Standard errors (reported in parentheses) are clustered by firm and by time. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1)	(2)	(3)	(4)	(5)
$D_{ASVIt-1} \times Dp_{t-1}$	**1.118****	**1.116****	**1.116****	**1.119****	**1.120****
	(0.514)	(0.517)	(0.518)	(0.520)	(0.520)
$D_{ASVIt-1}$	**-0.927**	**-0.930**	**-0.928**	**-0.932**	**-0.932**
	(0.595)	(0.597)	(0.597)	(0.601)	(0.601)
Dp_{t-1}	**3.713*****	**3.730*****	**3.905*****	**3.926*****	**3.928*****
	(0.224)	(0.228)	(0.239)	(0.244)	(0.244)
$Return_t$		**0.006*****	**0.006*****	**0.006*****	**0.006*****
		(0.001)	(0.001)	(0.001)	(0.001)
$Size_{t-1}$			**-0.066****	**-0.067****	**-0.063****
			(0.031)	(0.031)	(0.031)
MTB_{t-1}				**0.016*****	**0.016*****
				(0.003)	(0.003)
$Splitter_{t-12}$					**-0.494**
					(0.410)
Constant	**-9.109*****	**-9.129*****	**-8.334*****	**-8.375*****	**-8.415*****
	(0.258)	(0.262)	(0.480)	(0.483)	(0.484)
Observations	373,910	373,847	373,847	373,847	373,847
Pseudo R^2	0.143	0.143	0.144	0.145	0.145

Table 11
Gambling sentiment and IPO first-day returns

This table reports the underpricing of initial public offerings (IPOs). We run the following regressions:

$$r_t^{IPO} = \alpha + \beta_1 ASVI_{t-1} + \beta_2 p_{t-1} + \beta_3 VWMKT_t + \beta_3 Hotness_t + \beta_4 IPOnumber_t + \varepsilon_{t.}.$$

The dependent variable is the monthly average first-day return on the net IPOs obtained from Jay Ritter's website. Net IPOs are IPOs excluding closed-end funds, REITs, acquisition companies, stocks with offer prices below $5, ADRs, limited partnerships, units, banks and S&Ls, and those not listed on CRSP. First-day return is calculated as the percentage return from the offering price to the first closing bid price. The monthly average first-day return is calculated as the equal-weighted average of the first-day returns on all the offerings in a particular calendar month. Independent variables are the abnormal search volume intensity for the topic "Lottery" in the previous month ($ASVI_{t-1}$). Following Baker, Greenwood, and Wurgler (2009), we also include the average log price in the previous month (p_{t-1}) and the value-weighted return excluding dividends of all common stocks in the CRSP universe ($VWMKT_t$) as control variables. In addition, we control for the hotness of IPO market ($Hotness_t$, i.e., the percentage of deals that priced above the midpoint of the original file price range) and the natural logarithm of monthly number of net IPOs ($IPOnumber_t$). The sample period is from January 2005 to June 2014. *N months* reports the number of months. Standard errors (reported in parentheses) are adjusted for auto-correlation using the Newey and West (1987) method. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1)	(2)	(3)	(4)	(5)
$ASVI_{t-1}$	**6.445****	**7.022****	**7.233****	**8.402****	**8.093*****
	(3.163)	(3.417)	(3.406)	(3.367)	(3.090)
$VWMKT_t$		**0.516****	**0.487****	**0.405****	**0.414****
		(0.222)	(0.221)	(0.193)	(0.190)
p_{t-1}			**13.167*****	**14.310*****	**14.978*****
			(4.335)	(2.807)	(2.781)
$Hotness_t$				**0.166*****	**0.168*****
				(0.041)	(0.040)
$IPOnumber_t$					**-0.726**
					(1.766)
Constant	**13.432*****	**12.993*****	**-38.949****	**-49.672*****	**-50.776*****
	(1.290)	(1.307)	(17.384)	(11.448)	(10.672)
N months	107	107	107	107	107
Adjusted R^2	0.010	0.042	0.125	0.281	0.276

Table 12
Robustness checks

This table reports results for various robustness tests. Panels A and B consider the robustness with respect to the predictive power of our gambling sentiment measure. The dependent variables are the contemporaneous and future abnormal returns of a long-short portfolio. In Panel A, Columns 1 to 5 include U.S. monthly unemployment rate (*UNEMP*), unexpected inflation (*UEI*, i.e., current month inflation minus the average of the past 12 realizations), monthly growth in industrial production (*MP*), monthly default risk premium (*RP*, i.e., difference between Moody's Baa-rated and Aaa-rated corporate bond yields), or term spread (*TS*, i.e., difference between the yields of a constant maturity 10-year Treasury bond and 3-month Treasury bill) respectively as macroeconomic control. *ALL* (Column 6) reports the estimates by including all the five macroeconomic controls. Panel B considers subsets of data. Columns 1 and 2 consider a subsample from 2005 to 2010 when data on monthly investor sentiment index are available (Baker and Wurgler, 2007). Columns 3 and 4 consider the sample after June 2006, when Google's search volume intensity data become publicly available. We use Column 5 of Table 3 as the baseline specification. Panel C considers the robustness of our results for stock splits. Dependent variable is equal to one if the company splits its shares in a given month. Column 1 includes firm-level fixed effects. Columns 2 to 7 include the five macroeconomic variables as control variables. We use Column 5 of Table 8 as the baseline specification. Panel D considers the robustness of results related to IPO first-day return. The dependent variable is the monthly average first-day return on the net IPOs obtained from Jay Ritter's website. Columns 1 to 6 include macroeconomic controls. Standard errors (reported in parentheses) are adjusted for auto-correlation using the Newey and West (1987) method (Panels A, B, and D) or clustered by firm and by time (Panel C). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Return predictability with macroeconomic controls

Months	(1) UNEMP	(2) UEI	(3) MP	(4) RP	(5) TS	(6) ALL
0	**0.985**	**1.008**	**1.035**	**1.070**	**0.991**	**1.084**
	(0.962)	(0.996)	(0.969)	(0.974)	(0.964)	(1.026)
1	**2.364****	**2.368****	**2.440****	**2.493****	**2.357****	**2.506****
	(1.005)	(1.021)	(0.965)	(1.029)	(1.006)	(1.038)
2	**-1.369**	**-1.369**	**-1.269**	**-1.264**	**-1.372**	**-1.223**
	(1.027)	(1.022)	(1.115)	(1.017)	(1.024)	(1.110)
3	**-1.851****	**-1.864****	**-1.800****	**-1.755****	**-1.852****	**-1.739***
	(0.831)	(0.847)	(0.896)	(0.829)	(0.832)	(0.878)
N months	108	108	108	108	108	108

Table 12 (Cont'd)

Panel B: Return predictability with subsamples and investor sentiment control

Months	(1) 2005-2010	(2) 2005-2010	(3) After June 06	(4) After June 06
0	**1.234**	**1.235**	**0.830**	**0.871**
	(1.830)	(1.829)	(1.060)	(2.500)
1	**3.437*** **	**3.433*** **	**2.413** **	**4.127*** **
	(1.215)	(1.246)	(1.138)	(1.521)
2	**-1.836**	**-1.846**	**-1.013**	**-1.088**
	(1.522)	(1.540)	(1.104)	(2.028)
3	**-2.413**	**-2.420**	**-2.315** **	**-3.876** **
	(1.484)	(1.455)	(0.933)	(1.804)
Sentiment Control	NO	YES	NO	YES
N months	72	72	91	55

Panel C: Stock split with firm-level fixed effects and macroeconomic controls

Variables	(1) Firm FE	(2) UMEMP	(3) UEI	(4) MP	(5) RP	(6) TS	(7) ALL
$D_{ASVIt-1} \times Dp_{t-1}$	**1.248** **	**1.115** **	**1.121** **	**1.121** **	**1.116** **	**1.117** **	**1.114** **
	(0.634)	(0.519)	(0.520)	(0.520)	(0.519)	(0.519)	(0.518)
Controls	YES	YES	YES	YES	YES	YES	YES
Observations	38,100	373,847	373,847	373,847	373,847	373,847	373,847
Pseudo R^2	0.186	0.167	0.146	0.146	0.171	0.161	0.180

Panel D: IPO first-day return with macroeconomic controls

Variables	(1) UMEMP	(2) UEI	(3) MP	(4) RP	(5) TS	(6) ALL
$ASVI_{t-1}$	**7.982*** **	**8.066** **	**7.900** **	**8.000*** **	**7.765*** **	**7.561** **
	(3.000)	(3.133)	(3.113)	(2.952)	(2.903)	(3.040)
Controls	YES	YES	YES	YES	YES	YES
N months	107	107	107	107	107	107
Adjusted R^2	0.276	0.270	0.271	0.269	0.288	0.270

Figure 1
Search volume intensity for lottery

This figure plots the time-series of the search volume intensity (*SVI*) for the topic "Lottery" at the national level from January 2005 to December 2013. Points A to H correspond to the eight attention-grabbing jackpots. We define attention-grabbing jackpots in three different ways. First, the *all-time largest* jackpot is the $656 million jackpot announced on March 30, 2012, which is the largest jackpot in the U.S. history. Second, *record-breaking* jackpots are the jackpots that break national record at the time. They include the all-time largest jackpot and two other jackpots announced on February 18, 2006 and March 6, 2007. Third, we use a broader definition of *attention-grabbing* jackpots. In addition to the above three record-breaking jackpots, we include near-record jackpots that are either the second largest jackpot at the time or the largest jackpot over the past 24 months. Prize and date of the eight jackpots are reported in Appendix Table 1A. Source: Google Trends.

Panel A: National-level search volume intensity for "lottery"

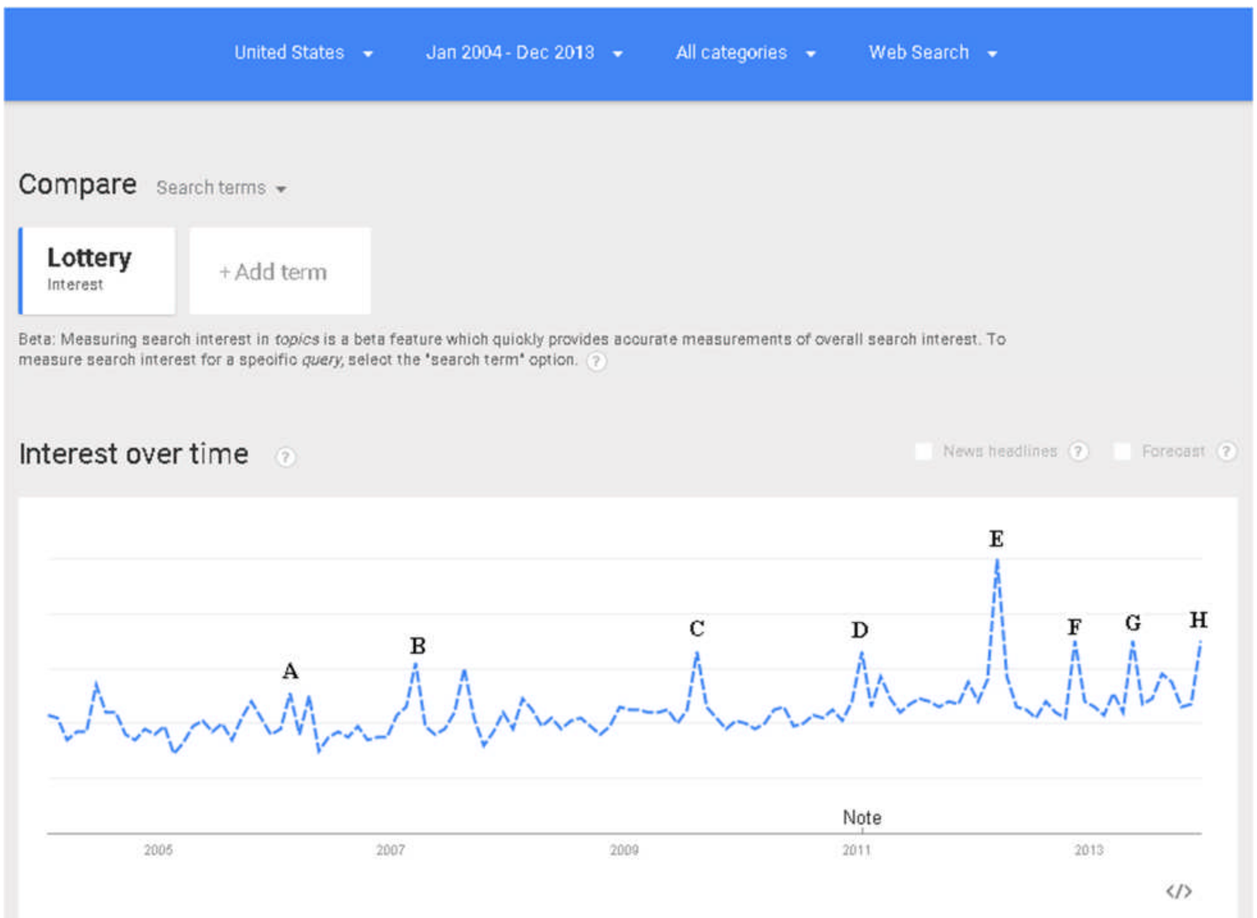


Figure 1 (Cont'd)

This panel plots the search volume intensity (*SVI*) for the topic "Lottery" for three U.S. states: Florida, Utah, and Texas. Points A and B correspond to jackpots of single state lotto games, while points C and D correspond to jackpots of multi-state lotto games. Source: Google Trends.

Panel B: State-level search volume intensity for "lottery"

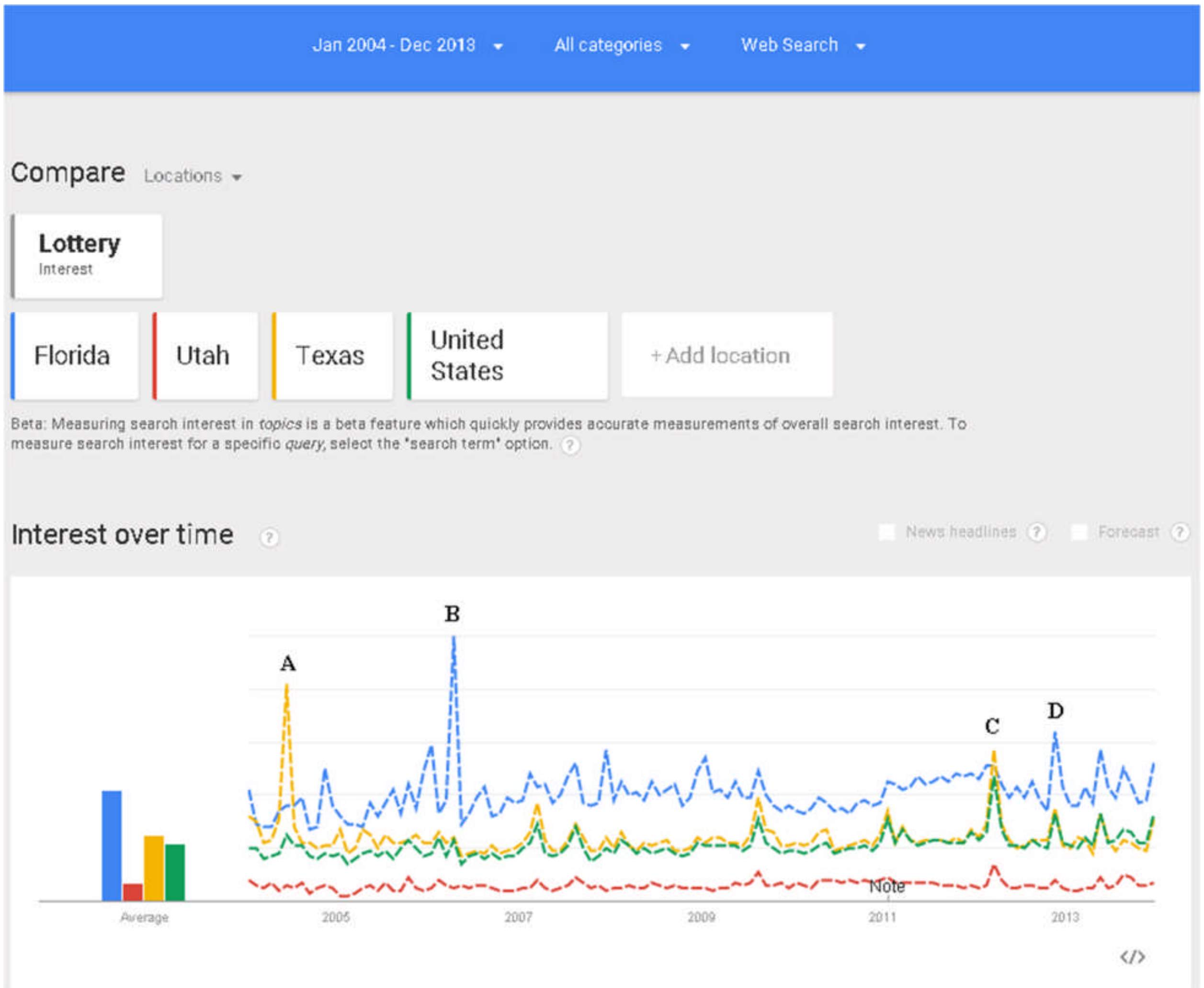
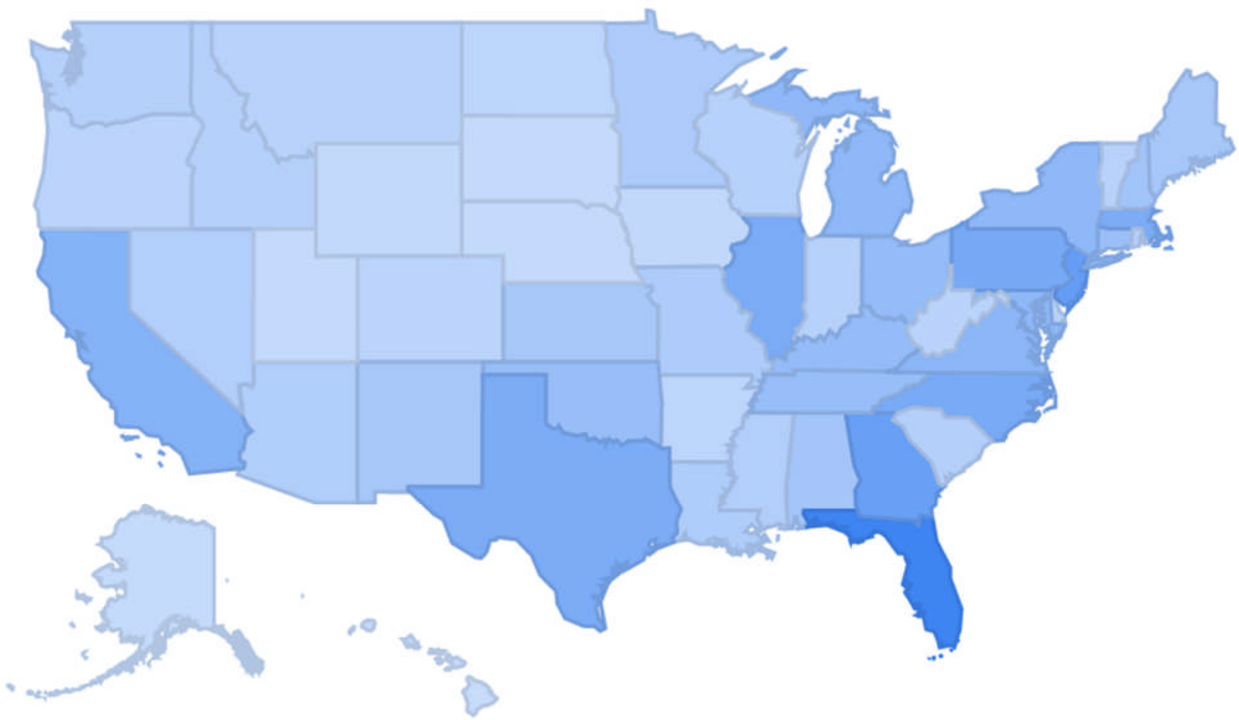


Figure 1 (Cont'd)

This panel shows the geographical distribution of the search volume intensity (*SVI*) for the topic "Lottery". Darker color indicates stronger search volume intensity. The intensity is calculated based on the average SVI during the 2004-2013 period. Source: Google Trends.

Panel C: Geographical distribution of search volume intensity for "lottery"



Appendix

Table 1A
Attention-grabbing jackpots

This table provides details about the eight attention-grabbing jackpots in our sample. *ID* corresponds to data points shown in Panel A of Fig. 1. *Jackpot date* is the final drawing day of the jackpot. *First date* is the first drawing day of the jackpot. *Value* is the prize of winning the jackpot in million dollars. *Game* is the corresponding lotto game of a jackpot. *Note* indicates whether the jackpot is the all-time largest, record-breaking, or attention-grabbing. We define the attention-grabbing jackpots in three different ways. First, the *all-time largest* jackpot is the $656 million jackpot announced on March 30, 2012, which is the largest jackpot in the U.S. history. Second, *record-breaking* jackpots are the jackpots that break national record at the time. They include the *all-time largest* jackpot and two other jackpots announced on February 18, 2006 and March 6, 2007. Third, we use a broader definition of *attention-grabbing* jackpots. In addition to the above three record-breaking jackpots, we include five near-record jackpots that are either the second largest jackpot at the time or the largest jackpot over the past 24 months. Source: Mega Millions, Powerball.

ID	*Jackpot date*	*First date*	*Value ($ m)*	*Game*	*Note*
A	Feb 18, 2006	Dec 17, 2005	365	Powerball	Record-breaking
B	Mar 6, 2007	Jan 12, 2007	390	Mega Millions	Record-breaking
C	Aug 28, 2009	Jul 10, 2009	336	Mega Millions	Near-record
D	Jan 4, 2011	Nov 12, 2010	380	Mega Millions	Near-record
E	Mar 30, 2012	Jan 27, 2012	656	Mega Millions	All-time largest
F	Nov 28, 2012	Oct 6, 2012	588	Powerball	Near-record
G	May 18, 2013	Apr 3, 2013	591	Powerball	Near-record
H	Dec 17, 2013	Oct 4, 2013	648	Mega Millions	Near-record