Searching for Gambles:
Gambling Sentiment and Stock Market Outcomes*

Yao Chen, *University of Exeter*
Alok Kumar, *University of Miami*
Chendi Zhang, *University of Exeter*

Abstract – Using Internet search volume for lottery to capture gambling sentiment shifts, we show that when the overall gambling sentiment is strong, investor demand for lottery stocks increases, these stocks earn positive short-run abnormal returns, managers are more likely to split stocks to cater to the increased demand for low-priced lottery stocks, and IPOs earn higher first day returns. Further, the sentiment-return relation is stronger among low institutional ownership firms, headquartered in regions where gambling is more acceptable and local bias is stronger. These results suggest that gambling sentiment has a spillover effect on the stock market.

JEL Classification: G11; G12; G14

Keywords: Gambling sentiment; lottery stocks; investor attention; catering; stock splits; IPO first day return.

* Alok Kumar can be reached at akumar@miami.edu. Yao Chen can be reached at y.chen5@exeter.ac.uk. Chendi Zhang can be reached at c.zhang@exeter.ac.uk. We thank two anonymous rerefees, Jawad Addoum, Nick Barberis, Hendrik Bessembinder (the editor), Linquan Chen, Zhi Da, Marc Goergen, Roman Kozhan, Jinfei Sheng, Richard Taffler, Jeff Wurgler, and seminar participants at the 2016 China International Conference in Finance, 2016 FMA Annual Meeting, 2016 EFMA Annual Meeting, 2019 Exeter Prize Workshop, Cardiff University, University of Exeter, University of Miami, University of Surrey, and University of Warwick for helpful comments and suggestions. All remaining errors and omissions are ours.

I. Introduction

An emerging literature in finance examines the potential link between gambling behavior and financial market outcomes. Theory predicts 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), and Barberis and Huang (2008)). Stocks with lottery like payoffs are overpriced in the short run 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. For example, Kumar, Page, and Spalt (2011) find that investors' gambling preferences varying 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. Attention to salient information on gambling events with large potential payoffs could motivate investors to become less risk averse. Prior literature from psychology and neuroscience documents that positive emotions, such as excitement generated by successful outcomes, induce individuals to take more risks and become more confident in future investment decisions (Bjork, Knutson, Fong, Caggiano, Bennett, and Hommer (2004), Kuhnen and Knutson (2011)). Kluger and DeNisi (1996) show that affective psychological reactions have "automatic and pervasive" effects on tasks in other settings. It is not clear, however, whether gambling sentiment *predicts* stock market outcomes.

We posit that gambling sentiment induced by large payoffs in one setting may influence individuals' investment decisions in other related economic settings. Specifically, we conjecture that an increase in overall sentiment toward gambling is likely to generate a positive spillover effect on investor demand for stocks with lottery characteristics, leading to positive price pressure on lottery stocks. Consequently, if arbitrage costs are high, the return of these stocks may be predictable in the short run. In addition, corporate financial decisions could be affected as firms respond to changes in investors' gambling attitudes and their impact on asset prices.

To directly test these conjectures, we develop a novel measure of investors' gambling sentiment based on Google's search volume intensity (SVI) on lottery related keywords. It measures the time variation in investors' overall propensity to gamble, and captures broader information than gambling events such as jackpot drawings or casino openings, which have been used in the recent literature.

We first examine 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 (2016), we define lottery 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), and Dorn and Sengmueller (2009)).

We conjecture that lottery stocks are likely to be more influenced by gambling sentiment than non-lottery stocks (i.e., stocks with high stock price, low idiosyncratic skewness, and low idiosyncratic volatility). Specifically, if stronger gambling sentiment induces risk taking behavior in the stock market, investor demand for lottery stocks would increase. As the arbitrage costs are likely to be high for lottery stocks given their low prices and high volatility, this excess demand in turn could generate price pressure on lottery stocks and generate positive abnormal returns in the short run (i.e. the spillover hypothesis).

Consistent with the spillover hypothesis, we find that when the gambling sentiment of investors becomes stronger, lottery stocks earn positive abnormal returns over the next two weeks. A one-standard-deviation increase in investors' gambling sentiment predicts an abnormal return of 11 basis points per week (5.4% per annum) for the lottery stock portfolio in two weeks' time. Importantly, the result is similar if we control for attention-grabbing jackpots in our gambling sentiment measure, suggesting that our measure contains value relevant information beyond information from jackpots. Further, the effect is 4 times larger around the 2008 financial crisis, consistent with investors having a greater propensity to gamble during recessions (Kumar (2009)).

To directly examine whether shifts in overall gambling attitudes affect investor demand for lottery stocks, we use two transaction level datasets to study investor trading behavior. We first use retail investors' trading data from a major U.S. discount brokerage firm (Barber and Odean, 2000) to study the impact of lottery jackpots on investor trading from 1991 to 1996. We find that large jackpots are associated with excess stock buy sell imbalance of 3% on the next trading day, which indicates a 3% increase in the net purchase of lottery stocks by retail investors relative to non-lottery stocks. Further, using TAQ data on stock transactions from 2004 to 2014 for the aggregate U.S. market, we show that large lottery jackpots are also associated with 0.37% excess order imbalance of lottery stocks next day, which has a smaller effect than those from retail trading data as TAQ covers the aggregate market including trades by institutional investors. Overall, our results on investor demand using retail and aggregate market data are consistent with our return predictability results, and suggest that stronger gambling sentiment would induce investors to take more risks in the stock market.

In the next set of tests, we examine the extent to which geographical differences in gambling sentiment influence the long-term performance of lottery stocks. As local investors' gambling sentiment varies across regions (Kumar et al. (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 stocks are more likely to be overpriced in the short run 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 state level SVI, which measures Internet searches from each state, to capture the gambling sentiment of local investors.

We find that in states with strong gambling sentiment, a trading strategy that goes long in lottery stocks and goes short in non-lottery stocks underperforms by 70 basis points per month (8.4% per annum) based on the Carhart (1997) four-factor model. The results are stronger for stocks with lower institutional ownership or headquartered in states with stronger local bias. In contrast, in U.S. states with relatively weaker gambling sentiment, lottery 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 stocks. Baker, Greenwood, and Wurgler (2009) show that 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 the low-priced stocks 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. The predicted probability of announcing stock splits for high-priced stocks is 0.07% per month higher following high gambling sentiment periods than low sentiment periods, which is economically significant given the average unconditional probability of stock splits of 0.10% per month.

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 demonstrates that IPOs are often perceived as lotteries by investors (Barberis and Huang (2008), Green and Hwang (2012)). 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 this conjecture, we find that a one-standard-deviation increase in investors' gambling sentiment is associated with a 1.36% increase in the average first day IPO return in the following month.

Overall, these findings suggest that changes in investors' gambling attitudes have a positive spillover effect on stock market outcomes. When investors' gambling sentiment becomes stronger, stocks with lottery characteristics earn positive abnormal returns in the short run as investor demand for these stocks increases, 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. Further, lottery stocks earn negative returns in the long run and the sentiment-return relation is stronger among low institutional ownership firms, headquartered in regions where gambling is more acceptable and local bias is stronger.

Our findings contribute to at least three distinct strands of finance literature. First, we contribute to the finance literature on skewness and gambling (e.g., Kumar (2009), Doran, Jiang, and Peterson (2012), Dorn, Dorn, and Sengmueller (2014), Gao and Lin (2014), and Liao (2017)). Our results provide new evidence on the potential link between the gambling market and the stock market. Previous studies examine investors' *ex-post* reactions to gambling events. Using a broader measure of investors' propensity to gamble, we find a positive spillover effect in the U.S. stock market. These findings suggest that shifts in gambling propensity over time *predict* stock returns, investor demand, and corporate policies.

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), (2015)). Specifically, we show that salient gambling events trigger strong gambling sentiment, which generates return predictability among lottery stocks.

Third, we add to the catering literature in corporate finance. In particular, our results provide new insights into the managerial motivation behind stock splits (e.g., Lakonishok and Lev (1987), Angel (1997), Baker et al. (2009)) and provide an alternative explanation for the time variation in first day IPO returns (e.g., Loughran and Ritter (2004)). Specifically, we show that firms cater to the time varying demand for lottery characteristics (i.e., low nominal share prices) by splitting stocks with high nominal share prices. In addition, we demonstrate that time variation in investors' gambling sentiment is an important determinant of first day IPO returns.

II. Hypotheses Development

We consider four different 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 stocks. The demand for lottery stocks can be positively correlated with that for lotteries (Kumar (2009)).[1] Doran et al. (2012) find that during periods with higher participation rates in conventional gambling activities, investors also have a higher demand for lottery stocks. Higher lottery ticket sales represent a higher enthusiasm for gambling and generate excess return comovement among lottery stocks (Kumar et al. (2016)). In addition, Liao (2017) finds that the opening of casinos motivates nearby retail investors to increase the idiosyncratic risk of their stock portfolios. Relatedly, Kearney (2005) shows that households in the U.S. would finance an increase in lottery spending by a reduction in none gambling expenditures such as food and rent, rather than by substituting expenditures away from other forms of gambling.[2] We posit

[1] A related economics literature on betting markets finds that state lotteries are complements to other forms of gambling. For example, the introduction of state lotteries increases the participation in casino gaming and horse racing (Scott and Garen (1994), Calcagno, Walker, and Jackson (2010)). In addition, different types of U.S. lotteries complement each other (Grote and Matheson (2007)).

[2] Another strand of literature shows that salient events in gambling markets could draw trading activities (measured by trading volume or market participation) away from the stock market. Gao and Lin (2014) show that retail investors in Taiwan reduce stock trading activities following large jackpots. Dorn et al. (2014) report similar evidence for jackpots in Germany, and mixed evidence for the U.S. market as it depends on the time periods and types of jackpots.

that, if lottery stocks are perceived as lotteries, investors are likely to invest disproportionally more in lottery stocks when gambling sentiment is strong, leading to positive price pressure on these stocks given arbitrage costs are likely to be high. To summarize, our first hypothesis posits:

H1 (Spillover hypothesis): Following periods of high gambling sentiment, lottery 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 investors with gambling attitudes are willing to accept a negative return premium for stocks with positively skewed returns. 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., with lower institutional ownership) and on firms headquartered in states with strong local bias. For stocks located in states with relatively weaker gambling attitudes, the negative lottery stock premium would be weaker or not existent.

To summarize, our second hypothesis posits:

H2: The effects of gambling sentiment on stock returns would be stronger in U.S. states with stronger gambling attitudes. Further, this impact is likely to be amplified among stocks with lower institutional ownership and firms headquartered in states with strong local bias.

It is worth noting that the evidence of reduced stock trading volume does not necessarily imply a negative pricing impact as stock market investors could reduce both buy and sell orders following large jackpots (Gao and Lin (2014)). In Sections IV.C and IV.D, we will discuss our results on the investor demand of lottery stocks following large jackpots in the U.S.

Our third hypothesis focuses on 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 et al. (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 split 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 investors. Since low nominal share price is a salient feature of lottery 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]

To summarize, our third hypothesis is:

H3: Firms with high share prices would exhibit a higher propensity to split their stocks when investors exhibit 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. IPOs could be perceived as lotteries, given their positively skewed returns (Barberis and Huang (2008), Green and Hwang (2012)). Hence the time variation in the IPO underpricing could be related to investors' gambling sentiment. If investors treat IPOs as lottery investment opportunities, they

[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 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).

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, our fourth hypothesis posits that:

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

III. Data and Methodology

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

A. Measures of Gambling Sentiment

Motivated by Da et al. (2011), we use the search volume intensity (SVI) for lottery related searches from Google to capture investors' gambling sentiment. Specifically, we use SVIs for the topic "Lottery" from Google Trends for the U.S region.[4] SVI measures the popularity of a 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. The time-series of SVI is available from 2004.

Following Da et al. (2011), our main variable is the abnormal search volume intensity (ASVI) for the topic "Lottery":

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

where $ASVI_t$ is the abnormal search volume intensity for the topic "Lottery" in time *t*. $LogSVI_t$ and $LogSVI_{t-1}$ represent the natural logarithm of SVIs in time *t* and time *t-1*, respectively. We use

[4] While the original Google search data reports search volume for a single text string, searches on topics provide a more comprehensive measure of overall attention by aggregating searches in different languages and different text strings to a single topic. Google Trends is available at http://www.google.com/trends/.

both monthly and weekly SVIs, depending on the appropriate frequency of the tests.[5] ASVI measures changes in people's attention toward lottery related events.

To study the geographical variation in gambling attitudes, we use the "interest by subregion" function in Google Trends to download the cross-sectional search interests in the topic "Lottery" during each calendar year.[6] We use the state level SVIs in the previous year to sort all U.S. states and Washington D.C. into two groups. We define a state or Washington D.C. as strong (weak) gambling sentiment states if it has above (below) median cross-sectional SVI in the previous year.

B. Validating the Gambling Sentiment Measure

To test whether our measure of gambling sentiment is reasonable, we obtain state lottery sales data and state level demographic data from the U.S. Census Bureau. State lottery sales data are from the 2017 annual survey of state government finances tables while state population data are from the 2017 U.S. population estimates. We collect news data from Factiva.

In the first validation test, we examine whether our measure of gambling sentiment correlates with news about state lotteries and other forms of gambling. Panel A of Figure A1 in the Appendix plots the "Lottery" SVI for the U.S. Using Factiva, we find that nearly all peaks (Points A to L) in the series coincide with the dates of the attention-grabbing jackpots from the two largest U.S. games, i.e., Mega Millions and Powerball. These jackpots are either record

[5] In the current version of Google Trends, the frequency of the search data depends on the selected time range. When choosing a time range that is longer than 5 years, Google will report monthly frequency SVI. In contrast, Google returns weekly frequency SVI when a time range shorter than 5 years is selected. Therefore, we download monthly frequency SVI by choosing 2004 to 2018 as our time range. To obtain weekly frequency SVI, we download weekly SVI in three subsamples: 2004 to 2008, 2009 to 2013, and 2014 to 2018. We specify the download period such that the adjacent time ranges share a common week, which we use to adjust the time-series to ensure comparability over time.

[6] The state level SVIs are calculated on a scale from 0 to 100 during the selected time frame (i.e., every calendar year). A higher value means a higher proportion of all search queries in that state, not a higher absolute query count. Therefore, they are comparable across states.

breaking or near record at the time. Details of these jackpots are reported in Table A2 in the Appendix.[7] As expected, the time-series correlation between ASVI and these jackpots is high at 55% (see Table A1 in the Appendix). Therefore, in our main empirical tests, we also use jackpot adjusted ASVI to study the incremental effects of gambling sentiment beyond attention-grabbing jackpots.[8] In unreported tests, we also find that other gambling events such as the Super Bowl, i.e. the biggest gambling event of a year, also raise SVI.

Next, we analyze how our state level SVI relates to the demographic characteristics of local investors. Table 1 presents the top five and bottom five states during the 2004 to 2018 period. Massachusetts has one of the highest levels of Catholic concentration and it also has one of the highest SVIs during our sample period. In contrast, Utah has the highest level of Mormon concentration and it has the lowest SVI. This is consistent with the findings of Kumar et al. (2011) who show that Catholics are more likely to gamble while Mormons have a strong opposition to gambling.

In 2017, the median lottery sales value is $3 billion for the top gambling sentiment states. This is 28 times greater than that of the bottom states. Similarly, the median per capita lottery sales ($303) for the top five gambling sentiment states is also about 3 times higher than that ($117) of

[7] It is important to note that large jackpots do not assure investor attention. The lottery literature (e.g., Williams and Siegel (2013)) shows that lottery players have jackpot fatigue: the excitement brought by a jackpot depends on its relative size with respect to other jackpots in the recent period. Investors could lose interest in buying lottery tickets even when the outstanding jackpot is large. In recent years, both Powerball and Mega Millions experience jackpot fatigue. Panel B of Figure A1 in the Appendix depicts the "Lottery" SVI for two large jackpots with similar size. When the national jackpot is $390 million, a near-record 336 million Mega Million jackpot in August 2009 raises SVI. In contrast, a $326 million jackpot in November 2014 does not attract attention as the national record increases to $656 million. Therefore, our gambling sentiment measure is a more direct measure of investor attention to gambling than jackpots.

[8] Table A1 in the Appendix reports the contemporaneous time-series correlations among ASVI and variables that are likely to affect investors' gambling propensity. These variables include a dummy variable that identifies attention-grabbing jackpots in Table A2, the Baker and Wurgler (2007) investor sentiment index, and the five commonly used macroeconomic variables. We find that ASVI has very low correlations with the investor sentiment index and the business cycle variables.

the bottom five states. Further, all the top five states have legalized state lotteries. In contrast, three out of the bottom five states have not adopted state lotteries by 2018 (i.e., no state lottery sales). This is consistent with the findings of Kumar et al. (2011) who show that regions with stronger gambling propensity legalize state lotteries earlier.[9] Overall, the validation test results indicate that our measure of gambling sentiment is reasonable, and captures broader information than proxies used in the prior literature.

C. Lottery Stocks

To analyze the influence of shifts in investors' gambling sentiment on stock market outcomes, we focus on lottery stocks for our first two economic settings. Our definition of lottery stocks follows that of Kumar et al. (2016), which is a continuous measure of the "lotteriness" of stocks. This measure is based on the theoretical framework developed in Harvey and Siddique (2000) and Barberis and Huang (2008). It is also motivated by the empirical definition of lottery stocks in Kumar (2009).[10]

Specifically, we use the following three measures to construct the Lottery Index (LIDX): nominal stock price, idiosyncratic skewness, and idiosyncratic volatility. Stock price is the closing price on the last trading day of the previous calendar year. Idiosyncratic skewness is the third moment of the residuals obtained by fitting a two-factor model using daily stock returns in the previous year, where the two factors are the excess market returns and the squared excess market returns. And, idiosyncratic volatility is the standard deviation of residuals from the Carhart (1997) model using daily stock returns in the previous year. We obtain price, return, and market

[9] We also report the geographical differences in gambling sentiment for each state during the 2004 to 2018 period in Panel C of Figure A1 in the Appendix. We find that the Internet search volume for the topic "Lottery" is higher in the West and the East coasts and is lower in the Central region.
[10] Our results remain quantitatively similar if we use MAX as an alternative definition of lottery stocks, as in Bali, Cakici, and Whitelaw (2011).

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.[11]

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).[12] Finally, we define lottery 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 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 stocks is $6.55, which is comparable in magnitude to the price of lottery tickets. Lottery stocks have a small average market capitalization of $306 million. As expected, they also have significantly higher volatility and skewness.

D. Data on Trading and Jackpots

To compare our results based on gambling sentiment with the effects of jackpots documented in the prior literature, we obtain trading data from both the Barber and Odean (2000) retail brokerage data and TAQ transaction level data for the aggregate market. The brokerage dataset contains all trades of a set of individual investors during the 1991 to 1996 period from a

---

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

[12] 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.

major U.S. discount brokerage house, while TAQ Monthly Product contains trading information of all investors till 2014.

We obtain date and prize of each jackpot drawing from the Multi-State Lottery Association and the USA Mega website. The only multi-state lotto game during the brokerage sample period is Powerball.[13] In comparison, there are two multi-state lotto games (i.e., Powerball and Mega Millions) during our TAQ sample from 2004 to 2014.

E. Institutional Ownership and Local Bias Data

Our second hypothesis posits that gambling sentiment would have a greater impact on stocks that are more likely to be held by retail investors (i.e., stocks with low institutional ownership) or headquartered in states with stronger local bias. Firm level institutional ownership data are collected from FactSet and based on Ferreira and Matos (2008).[14] We measure a firm's institutional ownership in a year by its average quarterly total domestic institutional ownership. The mean of total domestic 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.

We construct trading based local bias using Barber and Odean (2000) retail brokerage data (Kumar and Koniotis (2013)). Specifically, local bias is defined as the difference in average values between actual local turnover (i.e., the percentage of total investor turnover in a firm that is by local investors) and expected turnover (i.e, average state level trading volume in the last four quarters over shares outstanding last quarter). The former measures the percentage of total investor turnover that is local, while the latter captures the expected level of trading across states following

[13] Prior to April 22, 1992, Powerball was called Lotto America.
[14] We use FactSet to measure institutional ownership because it has a larger coverage than Thomson's 13f during our sample period from 2004 to 2018. Our results remain similar by using Thomson's 13f dataset.

the Coval and Moskowitz (2001) method. We sort all U.S. states and the Washington D.C. by local bias into three groups with 17 states or district in each group. We define strong (moderate) (weak) local bias using the top (medium) (bottom) 17 states or Washington D.C.[15]

F. Stock Splits Data

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. 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 711 stock splits from June 2004 to 2018. The average monthly probability of stock splits is 0.10% (see Panel B of Table 2).

G. 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", age of IPO firms, number of Internet IPOs, and the hotness of IPO markets from Jay Ritter's website.[16] The monthly average first day return is calculated as the equal-weighted average of the first day returns on all the offerings in a calendar month. During our sample period, the average IPO first day return is 13.72% (see Panel B of Table 2).

IV. Empirical results

[15] Our results are quantitatively similar by using a ownership-based local bias measure, defined as the difference in average values between state-level actual local ownership (i.e., the market value of local investors' holdings of firms headquartered in the state over the market value of all holdings by local investors) and expected ownership (i.e., the market value of all firms headquartered in the state over the market value of all firms).

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

A. Stock Return Predictability

Our first hypothesis focuses on the impact of time varying gambling attitudes on stock returns. If elevated gambling sentiment increases the demand for lottery stocks and generates price pressure on these stocks, ASVI should have a positive impact on the abnormal return of lottery stocks in the short run.

We use weekly returns in our return predictability tests, following Hou and Moskowitz (2005) and Da et al. (2011). To measure the abnormal return performance of lottery stocks, we use both the Carhart (1997) four-factor model and the Fama and French (2015) five-factor model as benchmarks. We estimate 52-week rolling window regressions and require all stocks to have at least 12 weeks of return data.[17] Stock level abnormal return is calculated as the difference between weekly actual return and return estimated using factor loadings. The abnormal returns are then value weighted to obtain the portfolio return.

Following Da et al. (2011), we estimate the following regression to determine if stock returns are predictable in the short run:

$$AR_{portfolio,t+n} = \alpha + \beta_n \times ASVI_t + \delta \times FSI_t + \epsilon_t, \qquad (n = 1, 2, 3, 4), \tag{2}$$

where $AR_{portfolio,t+n}$ is the average abnormal return in week $t+n$ of a stock portfolio weighted by market capitalization in week $t+n-1$, and FSI is the weekly financial stress index reported by the Federal Reserve Bank of St. Louis. The coefficient β_n measures the predictive power of ASVI with n lags.

Table 3 reports the results on return predictability tests. The coefficient estimates in Column 1 support a positive spillover effect. The β_n coefficients are positive in weeks 1 and 2 for the lottery stock portfolio, and statistically significant for week 2. In economic terms, a one-

[17] Our results remain similar if we use 156-week (i.e., 3 years) rolling window regressions.

standard-deviation increase (i.e., 17%) in the ASVI for the topic "Lottery" predicts a significantly positive price change of 11 basis points in week 2, which suggests that it takes a couple of weeks for gambling sentiment to have spillover effects on stock prices. The coefficient estimates become negative in weeks 3 and 4, indicating a subsequent price reversal as the mispricing gets corrected. In economic terms, a one-standard-deviation increase in ASVI significantly reduces lottery stocks' abnormal returns in week 4 by 10 basis points. In contrast to the lottery stock portfolio, ASVI does not have any power to predict the return of the non-lottery stock portfolio. Further, the estimates in Column 3 show that the return predictability is stronger when we Long lottery stocks and Short non-lottery stocks simultaneously.

To study to what extent the return predictive power of ASVI is driven by jackpots, we use an alternative method to construct ASVI and estimate return predictability regressions. Specifically, we regress our baseline ASVI on the attention-grabbing jackpot dummy and use the residuals as jackpot adjusted ASVI. As presented in Columns 4 to 6 of Table 3, we find that results are quantitatively similar after accounting for the effects of attention-grabbing jackpots. Further, Columns 7 to 9 of Table 3 show that our results remain robust when we use the Fama and French (2015) five-factor model to account for the impact of profitability and investment on lottery demand.

B. Stock Return Predictability During the Financial Crisis

Investors can exhibit a stronger propensity to gamble during financial crises (Kumar (2009)). If lottery stocks become more attractive during crisis periods, they could experience larger overpricing following a surge in gambling sentiment. In this subsection, we examine the impact of the 2008 financial crisis on lottery stock returns.

Specifically, we define the crisis period from July 2007 to March 2009, and estimate equation (2) for four subsamples: before the financial crisis, during the crisis, after the crisis, and excluding the crisis periods. We focus on the Long Short portfolio strategy. Panel A of Table 4 presents the coefficient estimates when using the Carhart (1997) four-factor model as the benchmark. We find that all the four subsamples have similar mispricing pattern to that in Table 3. In addition, consistent with our conjecture, the initial overpricing magnitude of lottery stocks is much larger during the financial crisis period. Economically, a one-standard-deviation increase in ASVI is associated with a significantly positive price change of 41 basis points in week 2, which is about four times larger than that in Table 3. Our results are similar when using the Fama and French (2015) five-factor model as the benchmark, as in Panel B of Table 4.

Overall, the results in Tables 3 and 4 support the spillover hypothesis (H1). Lottery stocks earn significantly positive abnormal returns when investors have stronger gambling sentiment. The magnitude of positive abnormal returns becomes larger during the financial crisis. This is consistent with a positive spillover effect that investors' gambling sentiment would generate short-term overpricing among lottery stocks.

C. Investor Demand for Lottery Stocks: Retail Investors

Our results so far suggest that lottery stocks are overpriced when the overall gambling sentiment is high. However, we have not yet shown that shifts in gambling attitudes are positively correlated with investor demand. Without this direct link, our results may have alternative explanations, especially because the evidence in recent studies (i.e., Dorn et al (2014), Gao and Lin (2014)) indicates that gambling and stock market trading volume may be negatively correlated.

In this section, we test directly whether retail investors increase demand for lottery stocks following large jackpots. We use the actual trades of retail investors from a large discount brokerage house during the 1991 to 1996 period, and aggregate them to the daily level.

To examine the impact of large jackpots on investor trading, we measure the retail demand for lottery stocks as the excess buy sell imbalance (EBSI) defined as the difference in the buy sell imbalance between lottery and non-lottery stock portfolios (Kumar (2009)).[18] This measure captures the change in investors' bullishness towards lottery stocks relative to their change in bullishness towards non-lottery stocks. We examine the spillover effect on the next trading day following a jackpot drawing. Specifically, we estimate the following time-series regression using all trade days during the January 1991 to November 1996 period:

$$(3) \qquad EBSI_t = \alpha + \beta_1 D_t^{Jackpot} + \beta_2 MKTRET_t + \beta_3 LOTRET_t + \beta_4 EBSI_{t-1} + \beta_5 VIX_{t-1} + \beta_6 ADS_{t-1} + CONTROLS + \epsilon_t.$$

The dependent variable is the daily excess buy sell imbalance for lottery stocks. Lottery stocks are defined as in Section III.C. The set of independent variables includes market return, return of the lottery stock portfolio, and lagged EBSI. Following Da et al. (2015), we also include the lagged Chicago Board Options Exchange daily market volatility index (VIX) to account for investor fear and market sentiment. Additionally, we include lagged Aruoba Diebold Scotti business conditions index (ADS) to capture the economic condition at the daily level since investors are known to have stronger gambling sentiment during economic recessions (Kumar (2009)). Control variables include lagged market and lottery stock portfolio returns (up to five

[18] The buy-sell imbalance (BSI) of portfolio p on day t is defined as $\mathrm{BSI_{pt}} = \frac{100}{\mathrm{N_{pt}}}\sum_{\mathrm{i=1}}^{\mathrm{N_{pt}}} \mathrm{BSI_{it}}$, where the BSI for stock i on day t is defined as $\mathrm{BSI_{it}} = \frac{\mathrm{VB_{it}} - \mathrm{VS_{it}}}{\mathrm{VB_{it}} + \mathrm{VS_{it}}}$. Here, VB_{it} (VS_{it}) is the dollar buying (selling) volume of stock i on day t, and N_{pt} is the number of traded stocks in portfolio p on day 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.

lags), day of the week dummies, and monthly time dummies. Standard errors are calculated using the method in Newey and West (1987).

The key variable of interest is $D_t^{Jackpot}$, which equals to one on the trading day following a large jackpot, or zero otherwise. We define a jackpot as a large (i.e., attention-grabbing) jackpot if its prize is ranked within the top 50 jackpots at the time of the drawing. Large jackpots correspond to approximately 10% of all trading days during the 1991 to 1996 period. Table 5 presents the results. We find a significantly positive coefficient of 3% on $D_t^{Jackpot}$, which suggests that large jackpots generate 3% more net purchase of lottery stocks on the following day relative to non-lottery stocks.[19]

D. Order Imbalance for Lottery Stocks: Aggregate Effects

In the next set of tests, we estimate equation (3) using TAQ data during the 2004 to 2014 period. We follow the Lee and Ready (1991) method to define buyer initiated and seller initiated transactions, and aggregate them from the second level to the daily frequency. We measure the aggregate demand for lottery stocks as excess order imbalance (EOIMB) defined as the difference in order imbalance between lottery and non-lottery stock portfolios. Order imbalance of a stock is calculated as the difference between buyer and seller initiated trading volumes. Specifically, we estimate the following time-series regression:

$$(4)\quad \text{EOIMB}_t = \alpha + \beta_1 D_t^{Jackpot} + \beta_2\text{MKTRET}_t + \beta_3\text{LOTRET}_t + \beta_4\text{EOIMB}_{t-1} + \beta_5\text{VIX}_{t-1} + \beta_6\text{ADS}_{t-1} + \text{CONTROLS} + \epsilon_t.$$

[19] We also examine the spillover effect from large Powerball jackpots in states that participated in Powerball during the 1991 to 1996 period, using zip codes to identify investor location. At the beginning of 1991, the Powerball lottery was offered in 15 states, which increased to 21 states by the end of 1996. In unreported tests, we study the subsample of trades after investor's' state offers Powerball. This leads to a 90% reduction in sample size, as large states in terms of stock trading such as New York and California are excluded. We still find a positive spillover effect in this small subsample, although it is statistically insignificant potentially due to the lack of statistical power. This small subsample could give noisy estimates of excess buy sell imbalance (EBSI) since relatively few households trade on a given trading day, and households can purchase Powerball tickets in neighboring states.

The dependent variable is the daily excess order imbalance for lottery stocks. We use the same set of independent variables as in equation (3). Standard errors are adjusted using the method in Newey and West (1987). The key variable of interest $D_t^{Jackpot}$ is a dummy variable that identifies large jackpots (i.e., those ranked within the top 50 jackpots at the time of drawing), which correspond to approximately 10% of all trading days during the TAQ data sample period. Table 6 presents the results. Consistent with brokerage results in Table 5, we find that a large jackpot is associated with 0.37% excess order imbalance for lottery stocks comparing to that of non-lottery stocks, which has a smaller effect than those from retail trading data as TAQ covers the aggregate market including trades by institutional investors.

Overall, the results in Tables 5 and 6 show that large jackpots motivate investors to increase their demand for stocks with lottery characteristics. This evidence suggests that shifts in gambling attitudes have a positive spillover effect on the U.S. stock market. The result is different from that from Gao and Lin (2014), who find a negative impact of large jackpots on stock trading volume in Taiwan. Further, it is also different from that of Dorn et al. (2014) who report insignificant results for the U.S. using trading volume data from TAQ during the 2004 to 2008 period.

The differences in results could arise from at least four reasons. First, using transaction level data, we directly study investor demand, measured by excess buy sell and order imbalance of lottery stocks following jackpots in the U.S., whereas previous studies analyze stock trading activities measured by trading volume and market participation. The evidence of reduced stock trading volume does not necessarily imply price pressure and return predictability as stock market investors could reduce both buy and sell orders following jackpots. For example, Gao and Li (2014), documenting a strong effect on trading volume from lottery jackpots in Taiwan, do not find a stock price impact.

Second, we use Google search volume to capture investors' overall propensity to gamble, which contains value relevant information even after controlling for jackpots. If focusing on the effects of attention-grabbing jackpots on investors' trading behavior, we also find a positive spillover effect. In contrast, the existing literature (Dorn et al (2014), Gao and Lin (2014)) use absolute jackpot size as a proxy for excitement. However, a large jackpot does not necessarily generate stronger gambling sentiment due to jackpot fatigue (see, e.g., Panel B of Figure A1 in the Appendix), which could bias their results against finding a positive spillover effect on the stock market. Third, we focus on a segment of the stock market which is relatively more likely to be positively affected by gambling sentiment, i.e. lottery stocks, whereas the prior literature studies the effects on the stock market overall, which could again bias against finding a spillover effect.

Last but not least, investors in different markets may react differently to gambling sentiment. For example, lottery players in Israel tend to overreact to large jackpots (Beenstock and Haitovsky (2001)) whereas those in the U.S. and U.K. tend to underreact (Creigh-Tyte and Farrell (2003), Matheson and Grote (2005)). Similarly, stock investors in different markets could also react differently to gambling sentiment. Therefore, the substitution effects documented in Taiwan and Germany may not be directly extrapolated to the U.S. setting.

E. State Level Gambling Sentiment and Return Predictability

Next, we study whether cross-sectional differences in gambling sentiment shifts affect stock performance in the long term. We use the state level SVIs in the previous year for the topic "Lottery" to capture cross-sectional variation in gambling sentiment and form portfolios based on the gambling sentiment of the state in which a firm is headquartered. Specifically, we define value-weighted portfolios for lottery and non-lottery stocks and then estimate the alphas of long short portfolios using monthly return regressions that include the Carhart (1997) four-factor model and Fama and French (2015) five-factor model as the benchmarks.

Panel A of Table 7 shows that lottery stocks significantly underperform non-lottery stocks. A trading strategy that Long lottery stocks and Short non-lottery stocks significantly underperforms the four-factor benchmark by 53 basis points per month. As expected, this effect is driven by firms headquartered in states with strong gambling sentiment, i.e., the Long Short strategy generates a negative return of -70 basis points per month (-8.4% per annum). In contrast, lottery and non-lottery stocks do not have significantly different performances when they are headquartered in U.S. states with weak gambling sentiment. We find similar results using the five-factor model as the benchmark, as reported in Panel B of Table 7.

We also examine cross-sectional differences among firms that are headquartered in states with strong gambling sentiment. Table 8 reports the long-term performance of stocks sorted by institutional ownership or local bias. Panel A shows that lottery stocks in strong gambling sentiment states have larger underperformance when the institutional ownership is lower. Specifically, lottery stocks underperform non-lottery stocks by about 2% per month for stocks with institutional ownership below ten percent. The return difference decreases to 55 basis points for stocks with above ten percent institutional ownership. In addition, Panel C shows that among stocks headquartered in states with strong local bias and strong gambling sentiment, lottery stocks significantly underperform non-lottery stocks by 74 basis points per month. In contrast, such underperformance does not exist for stocks headquartered in states with weak local bias even though gambling sentiment is strong. Further, we find quantitatively similar results by using the Fama and French (2015) five-factor model as the benchmark.

Collectively, the results in Tables 7 and 8 support our second hypothesis. Consistent with our conjecture, we find that in regions with strong gambling sentiment, local investors are willing to accept a more negative risk adjusted return for lottery stocks. This evidence is more pronounced among stocks with low institutional ownership or headquartered in states with strong local bias. In contrast, in U.S. regions with weak gambling sentiment, lottery stocks do not significantly underperform non-lottery stocks.[20]

F. Gambling Sentiment and Stock Splits

Previous finance 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), and Minnick and Raman (2014)). 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.

In this section, we use probit regressions 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 contemporaneous and lagged stock returns, lagged firm size, and book to market ratio. We also control for split activities in the previous twelve months. Specifically, we run the following logistic regression:

$$\text{(5)} \quad \text{Probit}(\text{SPLIT}_{i,t}) = \alpha + \beta_1 D_{ASVIt-1} + \beta_2 D_{Pi,t-1} + \beta_3 D_{ASVIt-1} \times D_{Pi,t-1} + \beta 4\text{RETURN}_{i,t}$$
$$+ \ \beta_5\text{RETURN}_{t-1} + \beta_6\text{SIZE}_{t-1} + \beta_7\text{BM}_{t-1} + \beta_8\text{SPLITTER}_{i,t-12} + \epsilon_t,$$

where $D_{ASVIt-1}$ is a dummy variable that equals one if investors have strong gambling sentiment. $Dp_{i,t-1}$ is a dummy variable of the price that equals one if a given stock is a high-priced stock. Following Baker et al. (2009), a high-priced stock has share price above the 70th price percentile

[20] We also examine to what extent idiosyncratic volatility could drive the stock performance results. In unreported tests, we find that while idiosyncratic volatility is an important factor for the return predictability of lottery stocks, it alone cannot fully explain the long-run underperformance of lottery stocks headquartered in strong gambling sentiment states and with low institutional ownership.

of all common stocks in the CRSP universe in a given month.[21] Similarly, we define strong gambling sentiment as ASVI values above the 70th percentile of all previous observations. $D_{ASVIt-1} \times Dp_{i,t-1}$ is the interaction between the price and the gambling sentiment dummy variables.

Among other variables, $\text{RETURN}_{i,t}$ ($\text{RETURN}_{i,t-1}$) is the return excluding dividends of stock *i* in month *t (t-1)*. $\text{SIZE}_{i,t-1}$ is the natural logarithm of the market capitalization of stock *i* in month *t-1* while $\text{BM}_{i,t-1}$ is the book to market ratio defined as the book value of the firm over its market value. $\text{SPLITTER}_{i,t-12}$ is a dummy variable that equals one if a firm split its stocks in the previous twelve months. 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 higher when the share price is high and gambling sentiment is strong.

Table 9 reports the estimation results. We find that $D_{ASVIt-1} \times Dp_{i,t-1}$ is positively significant in all specifications, which suggests that high-priced stocks split significantly more often during months following high gambling sentiment than during months following low sentiment, other things equal. Specifically, the predicted stock split probability following low gambling sentiment periods is 0.15% per month for high-priced stocks, which increases to 0.22% per month following high gambling sentiment periods, keeping other variables at the mean value. Hence the marginal effect (i.e. the difference between 0.22% and 0.15%) is 0.07%, statistically significant at the 1% level. This suggests that the probability of announcing stock splits for high-priced stocks increases by 0.07% per month following high gambling sentiment periods than low sentiment periods, which

[21] During our sample period, the average value of the 70th price percentiles is $31 with a minimum value of $13 and a maximum of $48. 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.

is economically significant given the average unconditional probability of stock splits of 0.10% per month.

In addition, $D_{ASVIt-1}$ is insignificant while $Dp_{i,t-1}$ is significant at the 1% level, which suggests that gambling sentiment affects the split probability only when the share price is high. We also find that small stocks and stocks with higher returns are more likely to split, which is consistent with the existing evidence in the literature. Further, our results remain quantitatively similar when we use jackpot adjusted ASVI to control for the effects of attention-grabbing jackpots, as shown in Column 6.

Overall, the evidence in Table 9 provides support to our third hypothesis. We demonstrate that 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.

G. First Day Return of IPOs

In this section, we focus on our fourth hypothesis and examine whether gambling sentiment helps to explain the time variation in first day IPO returns. We regress the average monthly first day return of the net IPOs against lagged ASVI. Specifically, we estimate the following regression:

$$\text{(6)} \quad R_t^{IPO} = \alpha+\beta_1 ASVI_{t-1} + \beta_2 HOTNESS_t + \beta_3 N_t^{Internet} + \beta_4 N_t^{IPO} + \beta_5 AGE_t^{IPO} + \beta_6 SENT_t + \beta_7 PEAD_t + CONTROLS + \epsilon_t.$$

Following Ibbotson et al. (1994), $HOTNESS_t$ is the percentage of deals that priced above the midpoint of the original file price range in month *t*. $N_t^{Internet}$ (N_t^{IPO}) is the natural logarithm of the monthly number of Internet IPOs (net IPOs) in month *t*. AGE_t^{IPO} is the natural logarithm of the average age of IPO firms. We also include the Baker and Wurgler (2007) investor sentiment index and the PEAD factor in Daniel, Hirshleifer, and Sun (2019) to account for the effects of investor sentiment and post earnings announcement drifts. Control variables include lagged average log price of all common stocks in the previous month, and contemporaneous and lagged value-weighted return of all common stocks, as in Baker et al. (2009).

Table 10 reports the estimation results. We find that the coefficient estimates of ASVI are positive and significant at the 5% level. A one-standard-deviation increase in ASVI (i.e., 19.7%) is associated with a 1.36% increase in the average first day IPO return. Relative to the mean first day return of 13.72%, this reflects an economically meaningful 9.91% increase. In addition, Column 6 shows that our results are similar after accounting for the effects of attention-grabbing jackpots. Consistent with our fourth hypothesis, this evidence suggests that when investors have stronger gambling sentiment, IPOs experience higher average first day returns.

H. Robustness Checks and Alternative Explanations

In this section, we conduct a number of robustness checks for our baseline results. First, we test whether our findings can be explained by other investor sentiment proxies. In Panel A of Table 11, Column 1 (2) reports the return predictability results without (with) the investor sentiment variable from Baker and Wurgler (2007). Our results are similar to the baseline return predictability estimates in Table 3, which suggests that our results on gambling sentiment cannot be explained by other investor sentiment measures.

Second, search volume intensity from Google was publicly available only after June 2006. Column 3 shows that our return predictability results are similar for the subperiod that starts in June 2006. In Column 4, we also control for the market-wide investor sentiment for this subperiod and our results remain similar. Thus, the stock return predictability patterns that we document exist even after Google's search data are made public.

Third, we test the robustness of the long-run underperformance of lottery stocks by using various (behavioral) asset pricing models. We first obtain data for the Stambaugh and Yuan (2016) four-factor mispricing model (M4 model, i.e., the market, size, MGMT, and PERF factors) from Stambaugh's website (available till 2016) and report results in Tables A3 and A4 in the Appendix. While Panel B of Table A3 shows that the negative lottery stock premium disappears for the full sample using the M4 model, the effect remains strong among stocks headquartered in strong gambling sentiment states with lower institutional ownership or stronger local bias (Panels B and D in Table A4). These results suggest that the M4 model does not fully explain the abnormal performance of lottery stocks headquartered in strong gambling sentiment states with more retail investor ownership or high local bias investor base. Further, the long-run underperformance of lottery stocks is robust to using the Daniel et al. (2019) three-factor behavioral factor (i.e., the market, PEAD, and FIN factors) model (see Tables A3 and A4 in the Appendix).

Fourth, we conduct several robustness checks for our stock split analysis. These results are summarized in Panel B of Table 11. In Columns 1 to 6, we include macroeconomic controls and our results still hold. In addition, we also use logit regressions to estimate our stock split tests and results remain the same (see Table A5 in the Appendix). Similar to the probit model results, the split probability for high-priced stocks increases by 0.06% per month during high gambling sentiment periods than low sentiment periods.

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 C of Table 11).

V. Summary and 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 stocks. Further, analyzing stock transaction data from a retail brokerage firm and the aggregate market data using TAQ, we show directly that investors increase aggregate demand for lottery stocks following large jackpots.

Examining geographical differences in the impact of gambling sentiment on market outcomes, we find that in U.S. states where gambling attitudes are strong, lottery stocks underperform stocks that are otherwise similar in the long run. These effects are stronger for firms headquartered in states with strong local bias and firms with lower institutional ownership.

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 IPOs. Collectively, these results suggest that shifts in overall gambling attitudes have positive spillover effects on financial markets.

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 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 stocks could experience more cash inflows when gambling sentiment is strong. It would also be interesting to examine the impact of gambling sentiment on hedge fund investors.

References

Angel, J.J., 1997. Tick size, share prices, and stock splits. *Journal of Finance* 52, 655-681.

Baker, H.K., Powell, G.E., 1992. Why companies issue stock splits. *Financial Management* 21, 11.

Baker, M., Greenwood, R., Wurgler, J., 2009. Catering through nominal share prices. *Journal of Finance* 64, 2559-2590.

Baker, M., Wurgler, J., 2007. Investor sentiment in the stock market. *Journal of Economic Perspectives* 21, 129-152.

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

Barber, B.M., Odean, T., 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. *Journal of Finance* 55, 773-806.

Barber, B.M., Odean, T., 2008. All that glitters: the effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies* 21, 785-818.

Barberis, N., Huang, M., 2008. Stocks as lotteries: the implications of probability weighting for security prices. *American Economic Review* 98, 2066-2100.

Beenstock, M., Haitovsky, Y., 2001. Lottomania and other anomalies in the market for lotto. *Journal of Economic Psychology* 22, 721-744.

Bjork, J.M., Knutson, B., Fong, G.W., Caggiano, D.M., Bennett, S.M., Hommer, D.W., 2004. Incentive-elicited brain activation in adolescents: similarities and differences from young adults. *Journal of Neuroscience* 24, 1793-1802.

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

Calcagno, P., Walker, D., Jackson, J., 2010. Determinants of the probability and timing of commercial casino legalization in the United States. *Public Choice* 142, 69-90.

Campbell, J.Y., Hilscher, J., Szilagyi, J., 2008. In search of distress risk. *Journal of Finance* 63, 2899-2939.

Carhart, M.M., 1997. On persistence in mutual fund performance. *Journal of Finance* 52, 57-82.

Coval, J.D., Moskowitz, T.J., 1999. Home bias at home: local equity preference in domestic portfolios. *Journal of Finance* 54, 2045-2073.

Coval, J.D., Moskowitz, T.J., 2001. The geography of investment: Informed trading and asset prices. *Journal of Political Economy* 109, 811-841.

Creigh-Tyte, S., Farrell, L., 2003. Is the UK national lottery experiencing lottery fatigue? In: Williams, L.V. (ed.), *The Economics of Gambling.* London and New York: Routledge, 165–181.

Da, Z., Engelberg, J., Gao, P., 2011. In search of attention. *Journal of Finance* 66, 1461-1499.

Da, Z., Engelberg, J., Gao, P., 2015. The sum of all fears investor sentiment and asset prices. *Review of Financial Studies* 28, 1-32.

Daniel, K., Hirshleifer, D., Sun, L., 2019. Short-and long-horizon behavioral factors. *Review of Financial Studies,* forthcoming.

Doran, J.S., Jiang, D., Peterson, D.R., 2012. Gambling Preference and the New Year Effect of Assets with Lottery Features. *Review of Finance* 16, 685-731.

Dorn, A., Dorn, D., and Sengmueller P., 2014. Trading as gambling. *Management Science* 61, 2376-2393.

Dorn, D., Sengmueller, P., 2009. Trading as entertainment? *Management Science* 55, 591-603.

Dyl, E.A., Elliott, W.B., 2006. The share price puzzle. *Journal of Business* 79, 2045-2066.

Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. *Journal of Financial Economics* 116, 1-22.

Ferreira, M.A., Matos, P., 2008. The colors of investors' money: the role of institutional investors around the world. *Journal of Financial Economics* 88, 499-533.

Gao, X., Lin, T.-C., 2014. Do individual investors treat trading as a fun and exciting gambling activity? Evidence from repeated natural experiments. *Review of Financial Studies* 28, 2128-2166.

Green, T.C., Hwang, B.-H., 2012. Initial public offerings as lotteries: skewness preference and first-day returns. *Management Science* 58, 432-444.

Grinblatt, M., Keloharju, M., 2001. How distance, language, and culture influence stockholdings and trades. *Journal of Finance* 56, 1053-1073.

Grinblatt, M., Keloharju, M., 2009. Sensation seeking, overconfidence, and trading activity. *Journal of Finance* 64, 549-578.

Harvey, C.R., Siddique, A., 2000. Conditional skewness in asset pricing tests. *Journal of Finance* 55, 1263-1295.

Hong, H., Kubik, J.D., Stein, J.C., 2008. The only game in town: stock-price consequences of local bias. *Journal of Financial Economics* 90, 20-37.

Hong, H., Scheinkman, J., Xiong, W., 2006. Asset float and speculative bubbles. *Journal of Finance* 61, 1073-1117.

Hou, K., Moskowitz, T.J., 2005. Market frictions, price delay, and the cross-section of expected returns. *Review of Financial Studies* 18, 981-1020.

Ibbotson, R.G., Sindelar, J.L., Ritter, J.R., 1994. The market's problems with the pricing of initial public offerings. *Journal of Applied Corporate Finance* 7, 66-74.

Kearney, M.S., 2005. State lotteries and consumer behavior. *Journal of Public Economics* 89, 2269-2299.

Kluger, A.N., DeNisi, A., 1996. The effects of feedback interventions on performance: A historical review, a meta-analysis, and a preliminary feedback intervention theory. *Psychological Bulletin* 119, 254.

Korniotis, G.M., Kumar, A., 2013. State-level business cycles and local return predictability. *Journal of Finance* 68, 1037-1096.

Kuhnen, C.M., Knutson, B., 2011. The influence of affect on beliefs, preferences, and financial decisions. *Journal of Financial and Quantitative Analysis* 46, 605-626.

Kumar, A., 2009. Who gambles in the stock market? *Journal of Finance* 64, 1889-1933.

Kumar, A., Lee, C.M.C., 2006. Retail investor sentiment and return comovements. *Journal of Finance* 61, 2451-2486.

Kumar, A., Page, J.K., Spalt, O.G., 2011. Religious beliefs, gambling attitudes, and financial market outcomes. *Journal of Financial Economics* 102, 671-708.

Kumar, A., Page, J.K., Spalt, O.G., 2016. Gambling and comovement. *Journal of Financial and Quantitative Analysis* 51, 85-111.

Lakonishok, J., Lev, B., 1987. Stock splits and stock dividends: why, who, and when. *Journal of Finance* 42, 913-932.

Lee, C.M.C., Ready, M.J., 1991. Inferring trade direction from intraday data. *Journal of Finance* 46, 733-746.

Liao, C., 2017. Risk taking begets risk taking: evidence from casino openings and investor portfolios. *Unpublished working paper*.

Lin, J.-C., Singh, A.K., Yu, W., 2009. Stock splits, trading continuity, and the cost of equity capital. *Journal of Financial Economics* 93, 474-489.

Loughran, T., Ritter, J., 2004. Why has IPO underpricing changed over time? *Financial Management* 33, 5-37.

Macey, J., O'Hara, M., Pompilio, D., 2008. Down and out in the stock market: the law and economics of the delisting process. *Journal of Law and Economics* 51, 683-713.

Matheson, V. and Grote, K., 2005. Rationality and efficiency in lotto games. In: Williams, L.V. (ed.), Information Efficiency in Financial and Betting Markets. Cambridge and New York: Cambridge University Press, 313–329.

Matheson, V., Grote, K., 2007. Examining the "halo effect" in lotto games. *Applied Economic Letters* 14, 307-310.

Minnick, K., Raman, K., 2014. Why are stock splits declining? *Financial Management* 43, 29-60.

Mitton, T., Vorkink, K., 2007. Equilibrium underdiversification and the preference for skewness. *Review of Financial Studies* 20, 1255-1288.

Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55, 703-08.

Odean, T., 1999. Do investors trade too much? *American Economic Review* 89, 1279-1298.

Palomino, F., Renneboog, L., Zhang, C., 2009. Information salience, investor sentiment, and stock returns: the case of British soccer betting. *Journal of Corporate Finance* 15, 368-387.

Scheinkman, J.A., Xiong, W., 2003. Overconfidence and speculative bubbles. *Journal of Political Economy* 111, 1183-1220.

Scott, F., Garen, J., 1994. Probability of purchase, amount of purchase, and the demographic incidence of the lottery tax. *Journal of Public Economics* 54, 121-143.

Seasholes, M.S., Zhu, N., 2010. Individual investors and local bias. *Journal of Finance* 65, 1987-2010.

Shefrin, H., Statman, M., 2000. Behavioral portfolio theory. *Journal of Financial and Quantitative Analysis* 35, 127-151.

Stambaugh, R.F., Yuan, Y., 2016. Mispricing factors. *Review of Financial Studies*, *30*, 1270-1315.

Weld, W.C., Michaely, R., Thaler, R.H., Benartzi, S., 2009. The nominal share price puzzle. *Journal of Economic Perspectives* 23, 121-42.

Williams, L.V., Siegel, D.S., 2013. *The Oxford handbook of the economics of gambling*. Oxford: Oxford University Press.

Woolridge, J.R., Chambers, D.R., 1983. Reverse splits and shareholder wealth. *Financial Management* 12, 5-15.

TABLE 1

Top and Bottom Gambling Sentiment States

This table reports characteristics of the top and bottom five states in terms of the average state level search volume intensity for the topic "Lottery" from 2004 to 2018. *SVI* is the average state level search volume intensity. ANNUAL_SALES (reported in million $) is the total lottery sales value in 2017. PER_CAPITAL_SALES is per capital lottery sales in dollar value, calculated as state level lottery sales divided by state population in 2017. N/A indicates that the state has not legalized state lotteries by 2018.

Panel A: Top Five States in Gambling Sentiment

State	(1) SVI	(2) ANNUAL_SALES	(3) PER_CAPITAL_SALES
New Jersey	95	3005	338
North Carolina	82	2259	220
Pennsylvania	76	3721	291
Massachusetts	74	5087	741
South Carolina	71	1520	303
Average	80	3118	379
Median	76	3005	303

Panel B: Bottom Five States in Gambling Sentiment

State	(1) SVI	(2) ANNUAL_SALES	(3) PER_CAPITAL_SALES
Utah	9	N/A	N/A
Hawaii	9	N/A	N/A
South Dakota	11	153	175
Montana	11	63	60
Alaska	12	N/A	N/A
Average	10	108	117
Median	11	108	117

TABLE 2
Summary Statistics

This panel reports the characteristics of lottery stocks, non-lottery stocks, and other stocks. Lottery 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 defined as the rest of stocks in CRSP. N_{Stock} reports the average number of lottery, non-lottery, other and all common stocks in the CRSP universe in each month. PRICE is the average stock price. RETURN is the monthly average realized stock return. MARKET_CAP is calculated as stock price multiplied by shares outstanding, reported in million U.S. dollars. BM is the book to market ratio defined as the book value of the firm over its market value. $VOLATILITY_{Idiosyncratic}$ is the standard deviation of the residual from the four-factor model using daily returns in the previous year. $SKEWNESS_{Total}$ (KURTOSIS) is the third (fourth) moment of daily stock returns. $SKEWNESS_{Idiosyncratic}$ is the scaled measure of the third moment of the residual from a two-factor model. N reports the number of firm month observations. The sample period is from June 2004 to December 2018.

Panel A: Characteristics of Lottery Stocks

Variables	(1) Lottery Stocks	(2) Non-Lottery Stocks	(3) Other Stocks	(4) All Stocks
N_{Stock}	1,162	1,224	1,615	4,002
PRICE	6.55	182.32	22.85	68.93
RETURN	0.66%	0.83%	0.82%	0.78%
MARKET_CAP	306.15	11,121.56	2,221.01	4,517.65
BM	1.04	0.57	0.74	0.77
$VOLATILITY_{Total}$	5.19%	1.89%	2.82%	3.25%
$VOLATILITY_{Idiosyncratic}$	5.08%	1.60%	2.59%	3.04%
$SKEWNESS_{Total}$	1.52	-0.26	0.25	0.48
$SKEWNESS_{Idiosyncratic}$	1.59	-0.31	0.37	0.53
KURTOSIS	14.80	4.77	7.28	8.78
N	186,219	215,500	278,181	679,900

TABLE 2 (Cont'd)

This panel reports the summary statistics of other variables for our empirical analyses. R^{IPO} 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. AGE^{IPO} is the natural logarithm of the average age of IPO firms. N^{IPO} ($N^{Internet}$) is the monthly number of IPOs (Internet IPOs). All the above variables are obtained from Jay Ritter's website. SPLIT is the monthly average splitting probability in percentage. 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., the 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). $IO_{Domestic}$ is the annual total U.S. institutional ownership. 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 June 2004 to December 2018.

Panel B: Other Variables

Variables	(1) MEAN	(2) STD_DEV	(3) 25^{th}_PCTL	(4) 50^{th}_PCTL	(5) 75^{th}_PCTL	(6) N
R^{IPO}	13.72	10.57	7.00	12.3	20.4	167
HOTNESS	36.86	23.64	21.00	39.00	50.00	167
AGE^{IPO}	2.62	0.58	2.32	2.67	3.03	170
N^{IPO}	9.88	6.58	4.00	10.00	14.00	175
$N^{Internet}$	1.15	1.34	0.00	1.00	2.00	175
SPLIT	0.10	0.11	0.03	0.06	0.12	175
UNEMP	6.25	1.91	4.70	5.40	8.00	175
UEI	0.00	0.33	-0.15	0.02	0.18	175
MP	0.08	0.72	-0.24	0.16	0.52	175
RP	1.07	0.48	0.82	0.92	1.17	175
TS	1.81	1.03	1.11	1.91	2.54	175
$IO_{Domestic}$	54.80	29.73	28.42	59.65	81.33	51,541

TABLE 3
Stock Return Predictability Regression Estimates

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":

$$AR_{portfolio,\ t+n} = \alpha + \beta_n ASVI_t + \delta FSI_t + \varepsilon_t,\ (n=1, 2, 3, 4).$$

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 52-week rolling window regressions. We use the Carhart (1997) four-factor model (C4, in Columns 1 to 6) and the Fama and French (2015) five-factor model (FF5, in Columns 7 to 9) as benchmarks. We then form value-weighted portfolios of lottery and non-lottery stocks. Lottery and non-lottery stocks are as defined in Table 2. Firms in lottery and non-lottery stock portfolios are rebalanced every January while portfolio weights are adjusted every month according to market capitalization in the previous month. β_n measure the predictive power of *ASVI* with *n* lags. We report the regression coefficients on ASVI (β_n) for lottery, non-lottery, and long short portfolios, respectively. Long Short is a portfolio strategy that goes long in lottery stocks and goes short in non-lottery stocks. Columns (1) to (3) and (7) to (9) report the results using baseline ASVI while Columns (4) to (6) report the results using jackpot adjusted ASVI. FSI is the weekly financial stress index reported by the Federal Reserve Bank of St. Louis. The sample period is from June 2004 to December 2018. *N* reports the number of weeks. The *t*-statistics computed using Newey and West (1987) adjusted standard errors are reported in parentheses below the estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	C4 Baseline ASVI			C4 Jackpot adjusted ASVI			FF5 Baseline ASVI		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Weeks	Lottery	Non-Lottery	Long Short	Lottery	Non-Lottery	Long Short	Lottery	Non-Lottery	Long Short
1	0.126	-0.030	0.156	0.096	-0.033	0.129	0.014	-0.019	0.033
	(0.424)	(-0.965)	(0.518)	(0.332)	(-0.902)	(0.440)	(0.046)	(-0.830)	(0.109)
2	0.632***	-0.033	0.665***	0.597**	-0.029	0.626**	0.716***	-0.034	0.750***
	(2.587)	(-1.190)	(2.583)	(2.154)	(-0.958)	(2.144)	(3.278)	(-1.429)	(3.295)
3	-0.136	0.002	-0.138	0.092	-0.007	0.099	0.046	-0.022	0.068
	(-0.578)	(0.054)	(-0.548)	(0.408)	(-0.212)	(0.405)	(0.200)	(-0.720)	(0.282)
4	-0.557**	0.058**	-0.615**	-0.710**	0.058*	-0.768**	-0.526***	0.060*	-0.586***
	(-2.326)	(2.015)	(-2.427)	(-2.443)	(1.934)	(-2.528)	(-2.772)	(1.890)	(-2.816)
N	761	761	761	761	761	761	761	761	761

TABLE 4
Stock Return Predictability Regression Estimates: Financial Crisis

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":

$$AR_{portfolio,\, t+n} = \alpha + \beta_n ASVI_t + \delta FSI_t + \varepsilon_t, \ (n=1, 2, 3, 4).$$

ASVI is the abnormal search volume intensity based on the time-series difference in log search volume intensities (see equation (1)). We use the Carhart (1997) four-factor model (C4, Panel A) and Fama and French (2015) five-factor model (FF5, Panel B) as benchmarks. We focus on a portfolio strategy that goes long in lottery stocks and goes short in non-lottery stocks. Lottery and non-lottery stocks are as defined in Table 2. β_n measure the predictive power of ASVI with n lags. Columns (1) to (4) report the regression coefficients on ASVI (β_n) before the financial crisis, during the crisis, after the crisis, and excluding the crisis periods, respectively. We define the financial crisis period from July 2007 to March 2009. FSI is the weekly financial stress index reported by the Federal Reserve Bank of St. Louis. The sample period is from June 2004 to December 2018. N reports the number of weeks. The t-statistics computed using Newey and West (1987) adjusted standard errors are reported in parentheses below the estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: C4

Weeks	(1) Pre-Recession Long Short	(2) Recession Long Short	(3) Post-Recession Long Short	(4) Non-Recession Long Short
1	0.239	-0.138	0.163	0.177
	(0.650)	(-0.195)	(0.394)	(0.548)
2	0.177	2.379**	0.651**	0.528*
	(0.361)	(2.122)	(2.129)	(1.940)
3	1.100*	-0.947	-0.475*	-0.078
	(1.904)	(-0.847)	(-1.727)	(-0.303)
4	-1.559***	-1.432	-0.208	-0.553**
	(-4.051)	(-1.361)	(-0.774)	(-2.168)
N	161	92	508	669

Panel B: FF5

Weeks	(1) Pre-Recession Long Short	(2) Recession Long Short	(3) Post-Recession Long Short	(4) Non-Recession Long Short
1	0.552*	0.216	-0.170	0.013
	(1.878)	(0.352)	(-0.439)	(0.040)
2	0.491	1.824*	0.716**	0.661***
	(1.242)	(1.675)	(2.583)	(2.805)
3	0.938**	-1.571	-0.063	0.191
	(2.486)	(-1.104)	(-0.214)	(0.823)
4	-1.082***	-0.198	-0.463*	-0.620***
	(-3.285)	(-0.197)	(-1.806)	(-2.980)
N	161	92	508	669

TABLE 5

Investor Demand for Lottery Stocks Following Large Jackpots: Retail Brokerage Data

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

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

$EBSI_t$ is the day t difference in the buy sell imbalance between lottery and non-lottery stocks. $D_t^{Jackpot}$ is a dummy variable that equals to one on trading days following large jackpots, and zero otherwise, where a jackpot is defined as a large jackpot if its prize is ranked within the top 50 jackpots at the time of the drawing. Other independent variables include market return, return of the lottery stock portfolio, and lagged EBSI. VIX_{t-1} is the lagged Chicago Board Options Exchange daily market volatility index. ADS_{t-1} is the lagged Aruoba Diebold Scotti business conditions index. Control variables include lagged market and lottery stock portfolio returns (up to five lags), day of the week dummies, and monthly time dummies. The sample period is from January 1991 to November 1996. *N* reports the number of trading days. The *t*-statistics computed using Newey and West (1987) adjusted standard errors are reported in parentheses below the estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
$D_t^{Jackpot}$	3.263*	3.176*	3.201*	3.146*	3.101*
	(1.835)	(1.786)	(1.789)	(1.743)	(1.724)
$MKTRET_t$	2.511**	5.378**	5.100**	5.075**	5.336**
	(2.251)	(2.093)	(1.998)	(1.993)	(2.100)
$LOTRET_t$		-2.661	-2.436	-2.476	-2.759
		(-1.345)	(-1.239)	(-1.255)	(-1.397)
$EBSI_{t-1}$			0.036	0.036	0.032
			(1.285)	(1.287)	(1.138)
VIX_{t-1}				0.272	0.357
				(0.555)	(0.736)
ADS_{t-1}					12.506***
					(2.707)
CONSTANT	22.233***	22.841***	21.991***	14.250	31.853*
	(3.771)	(3.921)	(3.830)	(0.955)	(1.917)
CONTROLS	Yes	Yes	Yes	Yes	Yes
N	1,492	1,492	1,492	1,492	1,492
Adjusted R^2	0.172	0.172	0.173	0.172	0.175

TABLE 6

Investor Demand for Lottery Stocks Following Large Jackpots: Aggregate Effects Using TAQ

This table reports the daily order imbalance (EOIMB) of lottery stocks following large Powerball and Mega Millions jackpots. We run the following time-series regression:

$$\text{EOIMB}_t = \alpha + \beta_1 D_t^{Jackpot} + \beta_2\text{MKTRET}_t + \beta_3\text{LOTRET}_t + \beta_4\text{EOIMB}_{t-1} + \beta_5\text{VIX}_{t-1} + \beta_6\text{ADS}_{t-1}$$
$$+ \text{CONTROLS} + \epsilon_t.$$

EOIMB_t is the day t difference in order imbalance between lottery and non-lottery stocks. $D_t^{Jackpot}$ is a dummy variable that equals to one on trading days following large jackpots, and zero otherwise, where a jackpot is defined as a large jackpot if its prize is ranked within the top 50 jackpots at the time of the drawing. Other independent variables include market return, the return of the lottery stock portfolio, and lagged EOIMB. VIX_{t-1} is the lagged Chicago Board Options Exchange daily market volatility index. ADS_{t-1} is the lagged Aruoba Diebold Scotti business conditions index. Control variables include lagged market and lottery stock portfolio returns (up to five lags), day of the week dummies, and monthly time dummies. The sample period is from June 2004 to December 2014. *N* reports the number of trading days. The *t*-statistics computed using Newey and West (1987) adjusted standard errors are reported in parentheses below the estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
$D_t^{Jackpot}$	0.539***	0.377**	0.382**	0.380**	0.373**
	(2.682)	(2.066)	(2.046)	(2.022)	(1.999)
MKTRET_t	0.586***	-1.938***	-1.962***	-2.011***	-2.006***
	(12.420)	(-10.063)	(-10.248)	(-10.546)	(-10.508)
LOTRET_t		2.542***	2.571***	2.584***	2.585***
		(12.875)	(13.167)	(13.343)	(13.354)
EOIMB_{t-1}			0.086***	0.085***	0.083***
			(4.123)	(4.133)	(4.047)
VIX_{t-1}				0.075***	0.069**
				(2.680)	(2.422)
ADS_{t-1}					1.354***
					(2.928)
CONSTANT	-12.649***	-12.451***	-11.411***	-12.594***	-12.048***
	(-41.915)	(-37.959)	(-28.793)	(-21.670)	(-19.863)
CONTROLS	Yes	Yes	Yes	Yes	Yes
N	2,664	2,664	2,664	2,664	2,664
Adjusted R^2	0.616	0.661	0.663	0.665	0.666

TABLE 7
Stock Performance among U.S. States Sorted by Gambling Sentiment

This table reports the performance of a value-weighted portfolio of lottery or non-lottery stocks. Abnormal return is measured as the intercept of monthly return regressions by using the Carhart (1997) four-factor model (C4, in Panel A) and the Fama and French (2015) five-factor model (FF5, in Panel B) as benchmarks. Full Sample reports the abnormal portfolio returns for all stocks in our sample. Strong (Weak) sentiment reports the abnormal portfolio returns of stocks headquartered in U.S. states with strong (weak) gambling sentiment. Strong – Weak measures the abnormal return difference between stocks located in states with strong and weak gambling sentiment. Strong (weak) gambling sentiment state group includes states with above (below) median search volume intensity for the topic "Lottery" in the previous year. The gambling sentiment sorted state groups are updated in January of each year. Long Short is a portfolio strategy that goes long in the lottery stock portfolio and goes short in the non-lottery stock portfolio. The sample period is from 2005 to December 2018. *N* reports the number of months. The *t*-statistics computed using Newey and West (1987) adjusted standard errors are reported in parentheses below the estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: C4

	(1) Lottery Stocks	(2) Non-Lottery Stocks	(3) Long Short
Full Sample	-0.505***	0.024	-0.529***
	(-2.993)	(0.869)	(-2.847)
Strong Sentiment	-0.699***	0.003	-0.702***
	(-3.761)	(0.057)	(-3.473)
Weak Sentiment	-0.182	0.062	-0.244
	(-0.747)	(0.841)	(-0.939)
Strong – Weak	-0.518**	-0.059	-0.458*
	(-1.988)	(-0.587)	(-1.702)
N	168	168	168

Panel B: FF5

	(1) Lottery Stocks	(2) Non-Lottery Stocks	(3) Long Short
Full Sample	-0.292*	-0.006	-0.286*
	(-1.835)	(-0.252)	(-1.668)
Strong Sentiment	-0.484***	-0.046	-0.438**
	(-2.748)	(-1.063)	(-2.399)
Weak Sentiment	-0.093	0.060	-0.154
	(-0.359)	(0.791)	(-0.545)
Strong – Weak	-0.390	-0.106	-0.284
	(-1.407)	(-1.012)	(-1.002)
N	168	168	168

TABLE 8

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 of monthly return regressions by using the Carhart (1997) four-factor model (C4, in Panels A and C) or the Fama and French (2015) five-factor model (FF5, in Panels B and D) as the benchmark. Panels A and B report 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 or non-lottery stocks with less (more) than ten percent institutional ownership. Panels C and D report the long-term performance of firms headquartered in U.S. states with different levels of local bias (LB). Strong LB (Weak LB) is the abnormal return of stocks headquartered in the top (bottom) 17 states sorted by local bias. Low – High (Strong – Weak) reports the abnormal return difference between the same types of stocks with different levels of institutional ownership (local bias). Long Short reports the abnormal return earned by a portfolio strategy that goes long in lottery stocks and goes short in non-lottery stocks. The sample period is from January 2005 to December 2018. *N* reports the number of months. The *t*-statistics computed using Newey and West (1987) adjusted standard errors are reported in parentheses below the estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Stocks Sorted by Institutional Ownership (C4)

	(1) Lottery Stocks	(2) Non-Lottery Stocks	(3) Long Short
Low IO	-2.036***	-0.006	-2.030***
	(-6.210)	(-0.025)	(-5.242)
High IO	-0.548***	0.005	-0.553**
	(-2.735)	(0.110)	(-2.562)
Low – High	-1.487***	-0.011	-1.477***
	(-4.208)	(-0.046)	(-3.684)
N	168	168	168

Panel B: Stocks Sorted by Institutional Ownership (FF5)

	(1) Lottery Stocks	(2) Non-Lottery Stocks	(3) Long Short
Low IO	-1.883***	-0.097	-1.786***
	(-5.780)	(-0.457)	(-4.549)
High IO	-0.328*	-0.043	-0.285
	(-1.677)	(-0.975)	(-1.418)
Low – High	-1.555***	-0.054	-1.501***
	(-4.456)	(-0.249)	(-3.770)
N	168	168	168

TABLE 8 (Cont'd)

Panel C: Stocks Sorted by Local Bias (C4)

	(1) Lottery Stocks	(2) Non-Lottery Stocks	(3) Long Short
Strong LB	-0.670***	0.073	-0.742***
	(-2.823)	(0.826)	(-3.029)
Weak LB	0.315	-0.261*	0.576
	(0.866)	(-1.973)	(1.398)
Strong – Weak	-0.985***	0.333**	-1.319***
	(-2.860)	(1.999)	(-3.296)
N	168	168	168

Panel D: Stocks Sorted by Local Bias (FF5)

	(1) Lottery Stocks	(2) Non-Lottery Stocks	(3) Long Short
Strong LB	-0.521**	-0.017	-0.504*
	(-2.042)	(-0.196)	(-1.940)
Weak LB	0.315	-0.242*	0.557
	(0.891)	(-1.915)	(1.376)
Strong – Weak	-0.836**	0.226	-1.061***
	(-2.407)	(1.483)	(-2.667)
N	168	168	168

TABLE 9

Gambling Sentiment and Stock Splits

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

$$\text{Probit}(\text{SPLIT}_{i,t}) = \alpha + \beta_1 D_{ASVIt-1} + \beta_2 D_{Pi,t-1} + \beta_3 D_{ASVIt-1} \times D_{Pi,t-1} + \beta 4\text{RETURN}_{i,t} + \beta_5\text{RETURN}_{t-1} + \beta_6\text{SIZE}_{t-1} + \beta_7\text{BM}_{t-1} + \beta_8\text{SPLITTER}_{i,t-12} + \epsilon_t.$$

The 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 ($D_{ASVIt-1} \times Dp_{i,t-1}$). $D_{ASVIt-1}$ is equal to one if $ASVI_{t-1}$ is above the 70th percentile of all previous observations. D_{pt-1} is equal to one if a firms' price is above the 70th percentile of all stock in the CRSP universe in a given month. Control variables include contemporaneous and lagged monthly returns ($\text{RETURN}_{i,t}$ and $\text{RETURN}_{i,t-1}$). We also include size ($\text{SIZE}_{i,t-1}$) and book to market ratio ($\text{BM}_{i,t-1}$) at the beginning of the month. $\text{SIZE}_{i,t-1}$ is the natural logarithm of the market capitalization of stock *i* in month *t-1* while $\text{BM}_{i,t-1}$ is defined as the book value of the firm over its market value. $\text{SPLITTER}_{i,t-12}$ is equal to one if a firm splits its share in the previous twelve months. Columns 1 to 5 report the results using baseline ASVI while Column 6 reports the results using jackpot adjusted ASVI. The sample period is from June 2004 to December 2018. *N* reports the number of firm month observations. The *t*-statistics computed using standard errors clustered by firm and by time are reported in parentheses below the estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$D_{ASVIt-1} \times D_{Pt-1}$	0.350**	0.347**	0.347**	0.347**	0.349**	0.367*
	(2.322)	(2.107)	(2.106)	(2.162)	(2.168)	(1.859)
$D_{ASVIt-1}$	-0.228	-0.228	-0.228	-0.229	-0.228	-0.288
	(-1.493)	(-1.352)	(-1.354)	(-1.398)	(-1.396)	(-1.466)
D_{Pt-1}	1.046***	1.081***	1.123***	1.090***	1.092***	1.106***
	(19.757)	(18.442)	(18.033)	(17.034)	(17.041)	(17.885)
RETURN_t		0.002***	0.002***	0.003***	0.003***	0.003***
		(4.442)	(4.388)	(5.630)	(5.628)	(5.792)
RETURN_{t-1}		0.004***	0.004***	0.003***	0.003***	0.003***
		(6.061)	(6.136)	(5.649)	(5.635)	(5.734)
SIZE_{t-1}			-0.015*	-0.040***	-0.040***	-0.040***
			(-1.864)	(-4.388)	(-4.280)	(-4.326)
BM_{t-1}				-0.747***	-0.756***	-0.755***
				(-12.232)	(-12.220)	(-12.135)
SPLITTER_{t-12}					-0.198*	-0.196*
					(-1.901)	(-1.899)
CONSTANT	-3.789***	-3.833***	-3.751***	-3.238***	-3.236***	-3.233***
	(-64.500)	(-58.556)	(-45.000)	(-35.876)	(-35.700)	(-36.561)
N	663,619	657,578	654,778	654,778	654,778	654,778
Pseudo R^2	0.130	0.135	0.135	0.155	0.155	0.154

TABLE 10
Gambling Sentiment and First Day IPO Returns

This table reports the predictive power of our gambling sentiment measure on first day returns of initial public offerings (IPOs). We run the following regressions:

$$R_t^{IPO} = \alpha+\beta_1 ASVI_{t-1} + \beta_2 HOTNESS_t + \beta_3 N_t^{Internet} + \beta_4 N_t^{IPO} + \beta_5 AGE_t^{IPO} + \beta_6 SENT_t + \beta_7 PEAD_t + CONTROLS + \epsilon_{t.}$$

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 $5, ADRs, limited partnerships, units, banks and S&Ls, and those not listed on CRSP. First day return is calculated as the percentage return from the offering price to the first closing bid price. The monthly average first day return is calculated as the equal-weighted average of the first day returns on all the offerings in a calendar month. Independent variables are the abnormal search volume intensity for the topic "Lottery" in the previous month ($ASVI_{t-1}$). We include the hotness of IPO market ($HOTNESS_t$, i.e., the percentage of deals that priced above the midpoint of the original file price range), monthly number of Internet IPOs ($N_t^{Internet}$), monthly number of IPOs (N_t^{IPO}), and the natural logarithm of average age of IPO firms (AGE_t^{IPO}) as control variables. We also control for the Baker and Wurgler (2007) investor sentiment index ($SENT_t$) and the PEAD factor in Daniel et al. (2019). Other control variables include average log price in the previous month, and contemporaneous and lagged value-weighted returns excluding dividends of all common stocks in the CRSP universe. Columns 1 to 5 report the results using baseline ASVI while Column 6 reports the results using jackpot adjusted ASVI. The sample period is from June 2004 to December 2018. *N* reports the number of months. The *t*-statistics computed using Newey and West (1987) adjusted standard errors are reported in parentheses below the estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$ASVI_{t-1}$	6.890**	6.884**	6.933**	6.819**	6.910**	7.707*
	(1.977)	(1.985)	(1.975)	(1.988)	(2.152)	(1.857)
$HOTNESS_t$	0.221***	0.221***	0.221***	0.219***	0.221***	0.220***
	(6.655)	(6.624)	(6.713)	(6.657)	(6.581)	(6.503)
$N_t^{Internet}$	1.344***	1.357***	1.332***	1.320***	1.342***	1.321***
	(3.234)	(3.303)	(3.339)	(3.208)	(3.259)	(3.130)
N_t^{IPO}		-0.006	0.005	-0.031	-0.060	-0.058
		(-0.054)	(0.042)	(-0.245)	(-0.465)	(-0.455)
AGE_t^{IPO}			-0.337	-0.252	-0.565	-0.729
			(-0.216)	(-0.165)	(-0.378)	(-0.478)
$SENT_t$				1.901	1.381	1.441
				(0.794)	(0.594)	(0.644)
$PEAD_t$					0.770	0.770
					(1.415)	(1.437)
CONSTANT	-20.315***	-20.305***	-18.994*	-19.628*	-16.431*	-15.824
	(-2.945)	(-2.906)	(-1.850)	(-1.964)	(-1.655)	(-1.590)
CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes
N	167	167	167	167	167	167
Adjusted R^2	0.307	0.302	0.298	0.297	0.311	0.308

TABLE 11
Robustness Checks

This table reports the results for various robustness tests. Panel A considers the robustness with respect to the predictive power of our gambling sentiment measure. The dependent variables are the future abnormal returns of a long short portfolio. Column 1 (2) reports the predictive power of our gambling sentiment measure without (with) investor sentiment index (Baker and Wurgler (2007)) as an additional control variable. Columns 3 and 4 consider the sample after June 2006, when Google's search volume intensity data become publicly available. We use Column 3 in Table 3 as the baseline specification. Panel B considers the robustness of our results for stock splits. We use Column 5 in Table 9 as the baseline specification. 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 C considers the robustness of results related to IPO first day return. We use Column 5 of Table 10 as the baseline specification. Columns 1 to 6 include macroeconomic controls. The *t*-statistics computed using Newey and West (1987) adjusted standard errors (Panels A and C) or standard errors clustered by firm and by time (Panel B) are reported in parentheses below the estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Return Predictability with Subsamples and Investor Sentiment Control

Weeks	(1) 2004 to 2018	(2) 2004 to 2018	(3) After June 06	(4) After June 06
1	0.156	0.155	0.160	0.158
	(0.518)	(0.516)	(0.458)	(0.453)
2	0.665***	0.664**	0.641**	0.638**
	(2.583)	(2.563)	(2.216)	(2.185)
3	-0.138	-0.139	-0.425*	-0.427*
	(-0.548)	(-0.551)	(-1.699)	(-1.704)
4	-0.615**	-0.617**	-0.379	-0.381
	(-2.427)	(-2.418)	(-1.465)	(-1.459)
SENT_CONTROL	No	Yes	No	Yes
N	761	761	656	656

Panel B: Stock Split with Macroeconomic Controls

Variables	(1) UMEMP	(2) UEI	(3) MP	(4) RP	(5) TS	(6) ALL
$D_{ASVIt-1} \times Dp_{t-1}$	0.351**	0.349**	0.349**	0.343**	0.349**	0.341**
	(2.177)	(2.169)	(2.169)	(2.141)	(2.162)	(2.120)
CONTROLS	Yes	Yes	Yes	Yes	Yes	Yes
N	654,778	654,778	654,778	654,778	654,778	654,778
Pseudo R^2	0.159	0.155	0.155	0.162	0.159	0.166

TABLE 11 (Cont'd)

Panel C: IPO First Day Return with Macroeconomic Controls

Variables	(1) UMEMP	(2) UEI	(3) MP	(4) RP	(5) TS	(6) ALL
$ASVI_{t-1}$	6.792**	6.887**	6.468**	6.944**	6.843**	6.337*
	(2.114)	(2.136)	(2.053)	(2.139)	(2.122)	(1.966)
CONTROLS	YES	YES	YES	YES	YES	YES
N	167	167	167	167	167	167
Adjusted R^2	0.314	0.308	0.316	0.308	0.307	0.310

Appendix

TABLE A1
Gambling Sentiment

This table reports the correlations between ASVI and variables that are likely to affect investors' propensity to gamble, all measured at monthly frequency. The first set of variables include five macroeconomic variables: 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). SENT is the Baker and Wurgler (2007) investor sentiment index. The jackpot dummy variable equals to one in months with attention-grabbing jackpots, or zero otherwise. Attention-grabbing jackpots are defined as those that break the national record or become the second largest jackpot at the time, or the largest jackpot over the past 24 months. Details of these jackpots are reported in Table A2 in the appendix. The sample period is from June 2004 to December 2018.

	ASVI	UNEMP	UEI	MP	RP	TS	JACKPOT
UNEMP	0.01						
UEI	0.02	0.04					
MP	0.01	0.03	0.05				
RP	0.03	0.35	-0.23	-0.49			
TS	0.00	0.71	0.00	-0.04	0.24		
JACKPOT	0.55	0.01	0.04	0.08	-0.03	-0.06	
SENT	0.00	-0.51	0.08	0.12	-0.48	-0.65	0.06

TABLE A2
Attention-Grabbing Jackpots

This table provides details about the twelve attention-grabbing jackpots in our sample. ID corresponds to data points shown in Panel A of Figure 1. Date is the final 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. Type indicates whether the jackpot is record breaking or near record. Record-breaking jackpots are the jackpots that break the national record at the time. They include the $1,586 million jackpot announced on January 13, 2016, and three other jackpots announced on February 18, 2006, March 6, 2007, and March 30, 2012. Near-record jackpots include eight 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	Date	Value ($ million)	Game	Type
A	19/10/2005	340	Powerball	Near-record
B	18/02/2006	365	Powerball	Record-breaking
C	06/03/2007	390	Mega Millions	Record-breaking
D	28/08/2009	336	Mega Millions	Near-record
E	04/01/2011	380	Mega Millions	Near-record
F	30/03/2012	656	Mega Millions	Record-breaking
G	28/11/2012	587.5	Powerball	Near-record
H	18/05/2013	590.5	Powerball	Near-record
I	17/12/2013	648	Mega Millions	Near-record
J	13/01/2016	1586	Powerball	Record-breaking
K	23/08/2017	758.7	Powerball	Near-record
L	23/10/2018	1537	Mega Millions	Near-record

TABLE A3

Stock Performance among U.S. States Sorted by Gambling Sentiment: Robustness

This table reports the performance of a value-weighted portfolio of lottery or non-lottery stocks. Abnormal return is measured as the intercept of monthly return regressions by using the Daniel, Hirshleifer, and Sun (2019) three-factor risk and behavioral model (BF3, in Panel A) and the Stambaugh and Yuan (2016) four-factor mispricing model (M4, in Panel B) as benchmarks. Full Sample reports the abnormal portfolio returns for all stocks in our sample. Strong (Weak) Sentiment reports the abnormal portfolio returns of stocks headquartered in U.S. states with strong (weak) gambling sentiment. Strong – Weak measures the abnormal return difference between stocks located in states with strong and weak gambling sentiment. Strong (Weak) gambling sentiment state group includes states above (below) median search volume intensity for the topic "Lottery" in the previous year. Gambling sentiment sorted state groups are updated in January of each year. Long Short is a portfolio strategy that goes long in the lottery stock portfolio and goes short in the non-lottery stock portfolio. The sample period is from 2005 to 2018 in Panel A and from 2005 to 2016 in Panel B. *N* reports the number of months. The *t*-statistics computed using Newey and West (1987) adjusted standard errors are reported in parentheses below the estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: BF3

	(1) Lottery Stocks	(2) Non-Lottery Stocks	(3) Long Short
Full Sample	-0.332	0.004	-0.336
	(-1.424)	(0.109)	(-1.296)
Strong Sentiment	-0.494*	-0.004	-0.490*
	(-1.932)	(-0.082)	(-1.741)
Weak Sentiment	-0.162	0.011	-0.173
	(-0.539)	(0.158)	(-0.542)
Strong – Weak	-0.332	-0.015	-0.317
	(-1.146)	(-0.154)	(-1.091)
N	168	168	168

Panel B: M4

	(1) Lottery Stocks	(2) Non-Lottery Stocks	(3) Long Short
Full Sample	-0.039	-0.009	-0.030
	(-0.213)	(-0.266)	(-0.150)
Strong Sentiment	-0.229	0.005	-0.234
	(-1.155)	(0.126)	(-1.076)
Weak Sentiment	0.227	-0.025	0.252
	(0.724)	(-0.331)	(0.751)
Strong – Weak	-0.456	0.030	-0.486
	(-1.387)	(0.319)	(-1.407)
N	144	144	144

TABLE A4
Performance of Stocks Headquartered in U.S. States with Strong Gambling Sentiment: Robustness

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 of monthly return regressions by using the Daniel, Hirshleifer, and Sun (2019) three-factor risk and behavioral model (BF3, in Panels A and C) or the Stambaugh and Yuan (2016) four-factor mispricing model (M4, in Panels B and D) as the benchmark. Panels A and B report 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 or non-lottery stocks with less (more) than ten percent institutional ownership. Panels C and D report the long-term performance of firms headquartered in U.S. states with different levels of local bias (LB). Strong LB (Weak LB) is the abnormal return of stocks headquartered in the top (bottom) 17 states sorted by local bias. Low – High (Strong – Weak) reports the abnormal return difference between the same types of stocks with different levels of institutional ownership (local bias). Long Short reports the abnormal return earned by a portfolio strategy that goes long in lottery stocks and goes short in non-lottery stocks. The sample period is from 2005 to 2018 in Panels A and C, and from 2005 to 2016 in Panels B and D. *N* reports the number of months. The *t*-statistics computed using Newey and West (1987) adjusted standard errors are reported in parentheses below the estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Stocks Sorted by Institutional Ownership (BF3)

	(1) Lottery Stocks	(2) Non-Lottery Stocks	(3) Long Short
Low IO	-1.665***	-0.029	-1.636***
	(-4.896)	(-0.125)	(-3.941)
High IO	-0.378	-0.002	-0.376
	(-1.385)	(-0.038)	(-1.262)
Low – High	-1.287***	-0.027	-1.260***
	(-3.645)	(-0.113)	(-3.094)
N	168	168	168

Panel B: Stocks Sorted by Institutional Ownership (M4)

	(1) Lottery Stocks	(2) Non-Lottery Stocks	(3) Long Short
Low IO	-1.573***	0.124	-1.697***
	(-4.297)	(0.500)	(-3.596)
High IO	-0.071	0.007	-0.078
	(-0.323)	(0.158)	(-0.326)
Low – High	-1.502***	0.118	-1.620***
	(-3.738)	(0.461)	(-3.225)
N	144	144	144

TABLE A4 (Cont'd)

Panel C: Stocks Sorted by Local Bias (BF3)

	(1) Lottery Stocks	(2) Non-Lottery Stocks	(3) Long Short
Strong LB	-0.444	0.093	-0.537
	(-1.300)	(0.970)	(-1.503)
Weak LB	0.572	-0.261*	0.834*
	(1.405)	(-1.895)	(1.786)
Strong – Weak	-1.017***	0.354**	-1.371***
	(-2.828)	(1.987)	(-3.302)
N	168	168	168

Panel D: Stocks Sorted by Local Bias (M4)

	(1) Lottery Stocks	(2) Non-Lottery Stocks	(3) Long Short
Strong LB	0.024	0.060	-0.036
	(0.095)	(0.753)	(-0.135)
Weak LB	0.878*	-0.165	1.043*
	(1.805)	(-1.173)	(1.972)
Strong – Weak	-0.854**	0.225	-1.079**
	(-2.119)	(1.315)	(-2.391)
N	144	144	144

TABLE A5
Gambling Sentiment and Stock Splits: Logit Model

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

$$\text{Logit}(\text{SPLIT}_{i,t}) = \alpha + \beta_1 D_{ASVIt-1} + \beta_2 D_{Pi,t-1} + \beta_3 D_{ASVIt-1} \times D_{Pi,t-1} + \beta 4\text{RETURN}_{i,t} + \beta_5 \text{RETURN}_{t-1} + \beta_6 \text{SIZE}_{t-1} + \beta_7 \text{BM}_{t-1} + \beta_8 \text{SPLITTER}_{i,t-12} + \epsilon_t.$$

The 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 ($D_{ASVIt-1} \times Dp_{i,t-1}$). $D_{ASVIt-1}$ is equal to one if $ASVI_{t-1}$ is above the 70th percentile of all previous observations. D_{pt-1} is equal to one if a firms' price is above the 70th percentile of all stock in the CRSP universe in a given month. Control variables include contemporaneous and lagged monthly returns ($RETURN_{i,t}$ and $RETURN_{i,t-1}$). We also include size ($SIZE_{i,t-1}$) and book to market ratio ($BM_{i,t-1}$) at the beginning of the month. $SIZE_{i,t-1}$ is the natural logarithm of the market capitalization of stock *i* in month *t-1* while $BM_{i,t-1}$ is defined as the book value of the firm over its market value. $SPLITTER_{i,t-12}$ is equal to one if a firm splits its share in the previous twelve months. Columns 1 to 5 report the results using baseline ASVI while Column 6 reports the results using jackpot adjusted ASVI. The sample period is from June 2004 to December 2018. *N* reports the number of firm month observations. The *t*-statistics computed using standard errors clustered by firm and by time are reported in parentheses below the estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
$D_{ASVIt-1} \times D_{Pt-1}$	1.307**	1.392*	1.385*	1.356**	1.358**	1.468*
	(2.082)	(1.876)	(1.876)	(1.975)	(1.979)	(1.727)
$D_{ASVIt-1}$	-0.942	-1.035	-1.030	-1.008	-1.007	-1.238
	(-1.465)	(-1.357)	(-1.357)	(-1.443)	(-1.442)	(-1.455)
D_{Pt-1}	3.698***	3.799***	3.923***	3.724***	3.728***	3.774***
	(17.686)	(16.565)	(16.647)	(15.937)	(15.947)	(16.673)
$RETURN_t$		0.005***	0.005***	0.007***	0.007***	0.008***
		(7.228)	(7.092)	(7.913)	(7.880)	(8.295)
$RETURN_{t-1}$		0.009***	0.009***	0.007***	0.007***	0.007***
		(5.494)	(5.655)	(6.351)	(6.332)	(6.410)
$SIZE_{t-1}$			-0.047*	-0.124***	-0.122***	-0.123***
			(-1.842)	(-4.344)	(-4.221)	(-4.268)
BM_{t-1}				-2.335***	-2.359***	-2.356***
				(-12.561)	(-12.551)	(-12.494)
$SPLITTER_{t-12}$					-0.571*	-0.565*
					(-1.734)	(-1.713)
CONSTANT	-9.488***	-9.608***	-9.355***	-7.680***	-7.678***	-7.669***
	(-40.134)	(-37.265)	(-30.521)	(-23.979)	(-23.905)	(-24.532)
N	663,619	657,578	654,778	654,778	654,778	654,778
Pseudo R^2	0.130	0.134	0.134	0.154	0.155	0.154

FIGURE A1

Search Volume Intensity for “Lottery”

This figure plots the time-series of the search volume intensity (SVI) for the topic “Lottery” in the U.S. region from 2004 to 2018. Points A to L correspond to the twelve attention-grabbing jackpots. We define attention-grabbing jackpots as those that break the national record or become the second largest jackpot at the time, or the largest jackpot over the past 24 months. The prize and date of the twelve jackpots are reported in Appendix Table A2. Source: Google Trends.

Panel A: National Level Search Volume Intensity for “Lottery”

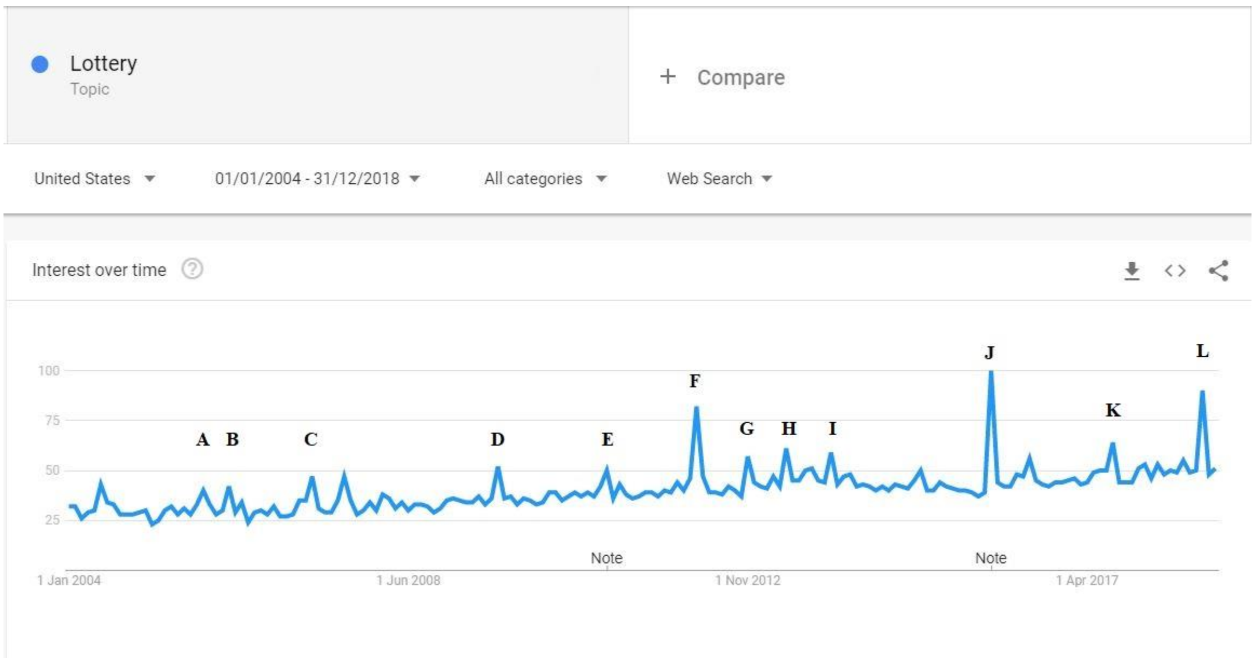

FIGURE A1 (Cont'd)

This panel plots the time-series of the search volume intensity (SVI) for the topic "Lottery" in the U.S. region from 2009 to 2014. Two Mega Million jackpots of similar sizes are labeled on the time-series: a $336 million jackpot in August 2009, and a $326 million jackpot in November 2014. Source: Google Trends, Mega Millions.

Panel B: Search Volume Intensity for "Lottery" of Jackpots with Similar Sizes

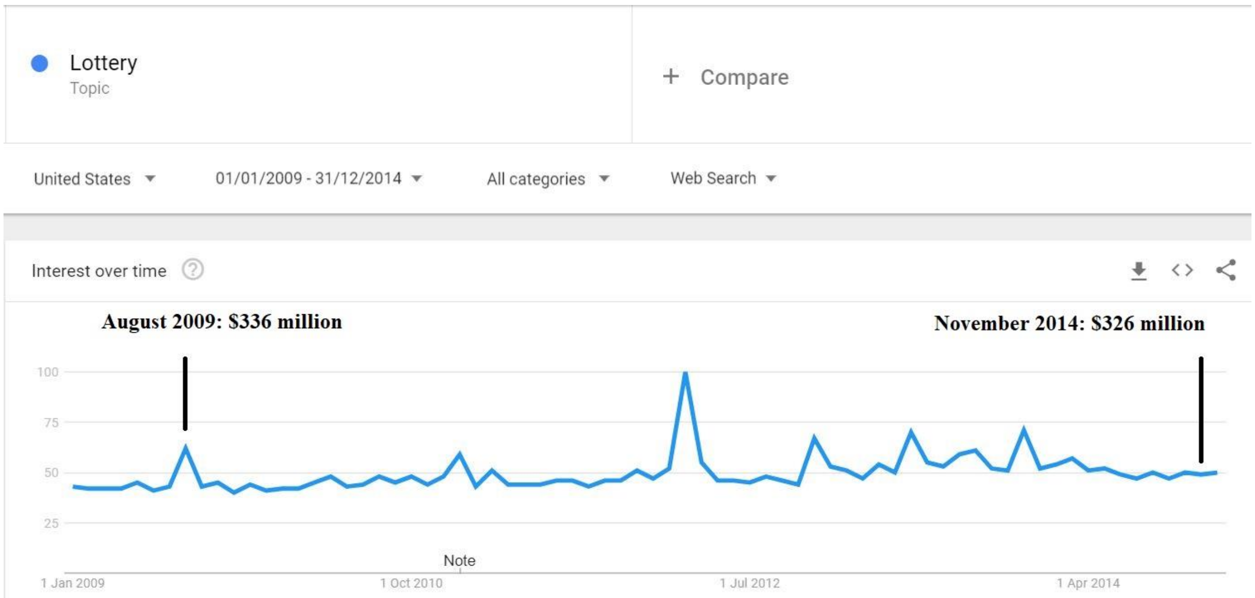

FIGURE A1 (Cont'd)

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 to 2018 period. Source: Google Trends.

Panel C: Geographical Distribution of Search Volume Intensity for "Lottery"