Time-Varying Demand for Lottery: Speculation Ahead of Earnings Announcements*

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Abstract

Existing studies find that compared to non-lottery stocks, lottery-like stocks tend to be overpriced and earn lower subsequent returns, probably due to investor preferences for lottery-like assets. We argue that investor preferences for holding speculative assets are more pronounced ahead of firms' earnings announcements, probably due to lower inventory costs and immediate payoffs or due to enhanced attention. We show that there is indeed stronger demand for lottery-like stocks ahead of earnings announcements, leading to a price run-up for these stocks. In sharp contrast to the standard underperformance of lottery-like stocks, we find that lottery-like stocks outperform non-lottery stocks by about 52 basis points in the 5-day window ahead of earnings announcements. However, this return spread is reversed by 80 basis points in the 5-day window after the announcements. Moreover, this inverted-V shaped pattern on cumulative return spreads is more pronounced among firms with more retail order imbalance, with low institutional ownership, and in regions with stronger gambling propensity.

JEL Classification: G02, G12, G14

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1 Introduction

Many studies find that investors exhibit a preference for speculative assets, and thus these assets tend to be overvalued on average, leading to underperformance of these stocks relative to non-speculative assets.[1] In this paper, we argue that investors' preferences for speculative stocks are time-varying, and are especially strong ahead of firms' earnings announcements. Because the positions are held only for a short period of time, trading ahead of earnings announcements reduces holding costs and inventory risk. Thus, speculative trading tends to increase prior to earnings announcements. Since lottery-like assets are especially good for speculation, the excess demand for these stocks should be notably higher especially before earnings announcements. In addition, earnings announcement events tend to grab retail investors' attention and lottery stocks are traded dominantly by retail investors, thus, the attention-driven demand for lottery stocks could be increased prior to earnings announcements.[2] Moreover, due to the inventory and idiosyncratic volatility concerns leading up to earnings announcements, the ability of arbitrageurs to act against the excess demand from noise traders is weakened.[3] Taken together, during the days ahead of earnings announcements, lottery-like assets should earn higher returns than non-lottery assets, which is exactly the opposite pattern of the usual underperformance of the lottery-like assets documented in the existing literature. Here, we use speculative assets and lottery-like assets interchangeably.

By contrast, after earnings announcements, we should expect the usual underperformance of lottery-like assets. This is because there are again two reinforcing mechanisms. First, investors might be surprised by negative earnings news associated with lottery-like stocks.[4]

[1] A partial list includes Barberis and Huang (2008), Boyer, Mitton, and Vorkink (2010), Bali, Cakici, and Whitelaw (2011), Green and Hwang (2012), Bali, Brown, Murray and Tang (2014), Conrad, Kapaida, and Xing (2014), and An, Wang, Wang, and Yu (2016), among others.

[2] For example, Drake, Roulstone, and Thornock (2012) show that investor attention measured by abnormal Google search is increased significantly ahead of earnings announcements. Aboody, Lehavy and Trueman (2010) provide evidence on the increase in investor attention before earnings announcements that can lead to the price run-up for stocks in the top percentile of past 12-month returns.

[3] For example, Berkman and McKenzie (2009) show that, on average, short sellers decrease their positions prior to earnings announcements and increase their positions shortly thereafter.

[4] Indeed, in untabulated analysis, we find that the expectation error is more severe for lottery-like stocks, suggesting that investors may not only overweight the small probability events, but they may also overestimate the small probability for large return outcomes. This is consistent with Fox (1999) who argues that individuals tend to both overweight and overestimate small probability outcomes. In addition, Brunnermeier, Gollier, and Parker (2007) show that investors' optimal belief could be overly optimistic about the probability of good states, leading to preferences for skewness. Thus, the more pronounced underperformance on and after announcement days could be partially due to the usual expectation errors, corrected upon the announcements.

Second, after the earnings announcements, uncertainty about the earnings news is resolved. Thus, potential concerns about inventory and idiosyncratic volatility also subside. As a result, the arbitrage forces are restored, and thus price reversal for lottery-like stocks is expected.

We empirically test this idea by the following procedure. We first choose a few popular proxies for the speculative feature of a stock. Following Kumar (2009), we choose stock price level, idiosyncratic volatility, and expected idiosyncratic skewness as our measures for the degree of speculativeness of a stock. In addition, the maximum daily return proposed by Bali, Cakici, and Whitelaw (2011) is also a proxy for speculativeness. They show that this measure is negatively associated with future stock returns in the cross-section. More recently, Conrad, Kapadia, and Xing (2014) show that jackpot probability is another good proxy for lottery features, and firms with high predicted jackpot probability tend to be overvalued on average and earn lower subsequent returns. Thus, we use these five popular proxies for a stock's speculative feature. In addition, based on these five individual proxies, we construct a composite z-score to proxy for the lottery feature.

Using these six measures, we find that the 5-day return spread between lottery-like stocks and non-lottery stocks is about 0.52% ahead of earnings announcements. In sharp contrast, the spread is reversed by 0.80% in the 5-day window after earnings announcements. Figure 1 plots the cumulative lottery spread during the (-5,+5) 11-day event window and presents the key results of our paper. This is consistent with the view that the stronger demand for lottery-like assets ahead of earnings announcements drives up their stock prices, and later on stock prices are reversed due to the diminished demand for lottery-like stocks to gamble after the news announcements and earnings surprises. Since most anomalies tend to be more pronounced during the earnings announcements,[5] the strong underperformance of the lottery-like stocks right after the earnings announcements is expected. However, the novel finding of our study is that ahead of the earnings announcements, we show a sharp price run-up for lottery-like stocks relative to non-lottery stocks. Most prior studies argue that lottery-like stocks could be overvalued and focus on the subsequent price reversal of these stocks. Our focus on pre-announcement periods provides useful information on the mechanism and the timing of the overvaluation in the first place and its subsequent corrections. In particular, we identify specific periods when the overvaluation is exacerbated, while prior studies mostly focus on the subsequent reversals.

[5]For a recent comprehensive study on anomaly returns around earnings announcements, see Engelberg, McLean, and Pontiff (2018).

One might argue that the more intense speculative trading behavior may also hold for other anomaly characteristics, and thus there is nothing special about our results on the inverted-V shaped cumulative lottery return spreads. For comparison, we also perform the same exercise for a set of prominent anomaly-related characteristics, in particular, value, momentum, profitability, and investment. We find that the cumulative return spreads based on book-to-market, past stock returns, profitability and the opposite of investment over assets are increasing *both* before and after earnings announcements. Thus, the inverted-V shaped cumulative return spread is unique to lottery-related characteristics. This contrast in the shape of cumulative return spreads highlights the unique role of speculation ahead of earnings announcements for our lottery-related characteristics. This result can also help us distinguish alternative potential explanations for our documented pattern. In particular, a reasonable explanation should invoke the special property of the lottery characteristic, rather than simply and exclusively rely on overall changes in short-sale activities or attention around the earnings announcement periods.

Due to short-sale constraints, stock prices tend to reflect optimistic opinions (Miller (1977)). Berkman, Dimitrov, Jain, Koch, and Tice (2009) find that stocks subject to high differences of opinion also have a price run-up prior to earnings announcements. One might argue that the dispersion of opinion is higher for lottery-like stocks, especially ahead of earnings announcements. Thus, due to short-sale constraints, there is a higher price run-up for lottery-like stocks ahead of earnings announcements. Using analyst forecast dispersion and share turnover as proxies for differences of opinion, we show that lottery-like stocks still outperform non-lottery stocks ahead of earnings announcements even after controlling for the differences of opinion. Thus, our results indicate that differences of opinion are not the key driving force for our documented pattern on the lottery-spread around earnings announcements.

To further investigate the underlying mechanisms for our findings during the pre-event window, we use transaction data to examine the change in retail trade imbalance for lottery-like assets before the earnings announcements. The daily retail trade imbalance is calculated as the difference between buy-initiated and sell-initiated small-trade volume divided by the total of buy-initiated and sell-initiated small-trade volume. We find that the retail trade imbalance increases significantly more for lottery-like stocks than non-lottery stocks ahead of earnings announcements. Since there is stronger buying pressure from retail investors before earnings announcements for lottery-like stocks, we observe a positive lottery return spread during this period. Thus, the pattern in retail trade imbalance before the earnings announcements is consistent with our findings on the return behavior for lottery-like and non-lottery stocks. Moreover, in Fama-MacBeth regressions, we find that the interaction term between retail trade imbalance and the lottery proxy is statistically significant in predicting pre-event 5-day returns, suggesting that the positive lottery effect is stronger when there is higher retail trade imbalance.

In addition to retail trade imbalance, we also use option data to gauge the gambling behavior around earnings announcements. In particular, we study the daily adjusted volume spread of short-term OTM call options relative to ATM call options during the (-5,+5) event window centered at the earnings announcement date. The adjusted volume for OTM (ATM) calls is defined as the percentage change of daily OTM (ATM) volume from its 3-month moving average, and the adjusted volume spread is the difference between the adjusted volume of OTM and ATM calls. We find that the adjusted volume spread increases ahead of earnings announcements and decreases after the announcements, consistent with the notion that the gambling behavior is more prominent ahead of earnings announcements.

Kumar, Page, and Spalt (2011) argue that gambling preferences would be stronger in regions with a higher concentration of Catholics relative to Protestants since the Catholic religion is more tolerant of gambling behavior. Indeed, they show that investors located in regions with a higher Catholic-Protestant ratio (CPRATIO) exhibit a stronger propensity to hold stocks with lottery features. Thus, if our positive lottery return spread ahead of earnings announcements is driven by the excess demand from investors with gambling preferences, we should expect that this positive lottery spread is higher for firms located in high CPRATIO regions where local speculative demand is expected to be stronger due to local bias. Using Fama-MacBeth regression analysis, we indeed confirm this hypothesis.

Since individuals tend to exhibit stronger preferences for lottery-like stocks, we expect this inverted-V shaped pattern on cumulative lottery return spreads to be more pronounced among firms with lower institutional ownership. In addition, lower institutional ownership impedes arbitrage forces more severely, and thus the price run-up for lottery-like stocks ahead of earnings announcements is also expected to be stronger among this group of stocks. Indeed, we find that the inverted-V shaped pattern is stronger among firms with lower institutional ownership, although it is still significant among firms with higher institutional ownership. We also investigate the pattern of our lottery return spreads around earnings announcements for other G7 countries. We find that the inverted-V shaped pattern around earnings announcements is similar across all the G7 countries except for Italy. Furthermore, we link the time-series variation of the lottery return spreads around earnings announcements to mutual fund flows and hedge fund flows. Consistent with Akbas, Armstrong, Sorescu, and Subrahmanyam (2015), we find that aggregate flows to mutual funds tend to exacerbate the price run-up for lottery stocks before earnings announcements, consistent with the notion that mutual fund flows appear to be dumb money. The opposite results hold for hedge fund flows.

Lastly, since the lottery-like stocks can outperform non-lottery stock ahead of earnings announcements, by taking this fact into account, one could improve the traditional strategy which bets against the lottery-like stocks. In particular, we should bet for lottery-like stocks ahead of earnings news and revert to the traditional betting-against-lottery strategy during other times. We show that this new strategy improves substantially upon the standard betting-against-lottery strategy. In particular, the monthly strategy return is improved from 1.09% to 1.50% for the composite lottery proxy.

In terms of related literature, our paper is related to a long list of anomaly papers on lottery. A large strand of literature documents that lottery-like assets have low subsequent returns. Boyer, Mitton, and Vorkink (2010) find that expected idiosyncratic skewness and future returns are negatively correlated. Bali, Cakici, and Whitelaw (2011) show that maximum daily returns in the previous month are negatively associated with future returns.[6] More recently, Conrad, Kapaida, and Xing (2014) document that firms with a high probability of extremely large returns (i.e., jackpot) usually earn abnormally low future returns. All of these empirical studies suggest that positively skewed stocks can be overpriced and earn lower future returns.[7] In contrast to this literature, we show that lottery-like stocks actually outperform non-lottery stocks ahead of earnings announcements. We also show that by taking this pre-announcement pattern into account, we can improve the traditional lottery strategy significantly. Further, Doran, Jiang, and Peterson(2011) show that investors' preferences for lottery features is stronger during January due to the New Year gambling effect and lottery-like stocks outperform in January. Our study differs by investigating the news-driven time-variation in lottery demand.

Our paper is also related to a recent study by Rosch, Subrahmanyam, and van Dijk (2016). They hypothesize that stock-specific information events (such as earnings announcements)

[6]Bali, Cakici, and Whitelaw (2011) and Bali, Brown, Murray and Tang (2014) argue that preferences for lottery-like stocks can also account for the puzzle that firms with low volatility and low beta tend to earn higher risk-adjusted returns.

[7]In addition, several studies have employed options data to study the relation between alternative skewness measures and future returns. For instance, see Xing, Zhang, and Zhao (2010), Bali and Murray (2013), and Conrad, Dittmar, and Ghysels (2013).

may affect price efficiency because inventory and idiosyncratic volatility concerns leading up to the event could temporarily challenge the ability of arbitrageurs to act against predictable patterns in returns and price deviations from the efficient market benchmark. Thus, the stock market is less efficient ahead of earnings announcements. Our results are consistent with their general view since lottery-like stocks are indeed more overvalued ahead of earnings news. We differ from them by focusing on one specific set of firm characteristics, i.e., firm-level lottery features, and we provide an in-depth study of investor demand for lottery around earnings announcements.

Prior studies find that most anomalies tend to be more pronounced around earnings announcements. For example, La Porta, Lakonishok, Shleifer, and Vishny (1997) find that the value strategy performs much better around earnings announcements. Berkman, Dimitrov, Jain, Koch, and Tice (2009) find that firms with high differences of opinion earn significantly lower returns around earnings announcements than firms with low differences of opinion. More recently, Engelberg, McLean, and Pontiff (2018) use a large set of stock return anomalies and find that anomaly returns are about 6 times higher on earnings announcement dates. On the one hand, the pattern of more pronounced anomaly returns around earnings announcements is consistent with biased expectations, which are at least partially corrected upon news arrival. On the other hand, this pattern could also be consistent with a disproportionally large risk associated with earnings news. However, our results are hard to reconcile with a pure risk-based story since the sign on the return spread has switched before and after the event. It is hard to build a risk-based model where lottery-like stocks are more risky before earnings announcements and less risky after earnings announcements.[8] Lastly, our paper is also related to So and Wang (2015) which studies short-term return reversal effect ahead of earnings announcements. They argue that market makers demand higher expected returns for the liquidity provision prior to earnings announcements because of the increased inventory risk ahead of the anticipated earnings news. Indeed, they document a strong increase in short-term return reversals ahead of earnings announcements. We differ by focusing on the time-varying demand for lottery-like stocks rather than time-varying liquidity provision. Moreover, while they show the short-term reversals effect is *stronger* ahead of earnings announcements, we show that the lottery-return spread is *reversed* ahead

[8]There might be some exceptions though. For example, Barber, DeGeorge, Lehavy, and Trueman (2013) argue that the earnings announcement premium could be due to the idiosyncratic risk that can not be diversified away. An elaborated model based on their argument could potentially generate a higher price run-up for the lottery stocks than nonlottery stocks before earnings announcements. However, for a pure risk-based story to convincingly explain our pattern, the model needs to produce lower returns for lottery stocks than nonlottery stocks after earnings announcements, and also the lack of inverted V-shape around earnings announcements for other anomalies such as the profitability premium at the same time.

of earnings announcements, compared to other periods.

2 Data and Definitions of Key Variables

This section describes our data sources and empirical measures. We also provide summary statistics for our key variables used in our subsequent analysis.

2.1 Data

Our sample includes quarterly earnings announcements made by firms listed on the NYSE, AMEX, and NASDAQ from January 1972 to December 2014. To reduce the potential effects of penny stocks, we delete stocks with a price less than $1 per share at the end of the month prior to the earnings announcements. Our data come from several data sources. Earnings announcement dates are from the Compustat Quarterly files. Stock returns data are from CRSP and accounting data are from Compustat. Analyst data are from the Institutional Brokers Estimates System (IBES) from 1985 to 2014.[9] Institutional ownership data are from the Thomson Financial 13F file from 1980 to 2014. The transaction data are from the Institute for the Study of Securities Market (ISSM) from 1983 to 1992 and the Trade and Quote (TAQ) data from 1993 to 2000 for NYSE and AMEX common stocks.[10] Monthly mutual fund total net assets and returns data come from CRSP Survivor-Bias-Free US Mutual Fund Database. Monthly hedge fund total net assets and returns data come from the Thomson Reuters Lipper Hedge Fund (TASS) Database. Religious composition data are from "Churches and Church Membership" files from the American Religion Data Archive (ARDA). Options data are from the OptionMetris database. Our international stock and accounting data come from Compustat Global database. The earnings announcement dates for international companies are from Thomson Reuters Worldscope, Bloomberg, and Compustat North American database. To ensure the data quality of earnings announcement dates for international companies, we use multiple databases to validate the dates. In particular, we only use dates to exist in both Thomson Reuters Worldscope database and

[9]Following Berkman et al. (2009), our IBES data starts from 1985 due to the insufficient data prior to that year.

[10]We follow previous literature (Barber, Odean, and Zhu (2009)) to restrict our analysis to the sample period of 1983 to 2000 for NYSE/AMEX stocks, because it's not appropriate to distinguish institutional from retail trades based on the order size after the decimalization since 2000, and the trading mechanism is different in NASDAQ.

Bloomberg for other G7 countries except for Canada, for which we require the dates to exist in all three data sources: Thomson Reuters Worldscope database, Compustat North American database and Bloomberg.

2.2 Lottery Measures

For US stocks, we use six variables to proxy for the lottery feature of stocks following prior studies. These measures include the maximum daily return (Maxret), expected idiosyncratic skewness (Skewexp), stock price (Prc), the probability of jackpot returns (Jackpotp), idiosyncratic volatility (Ivol), and a composite z-score (Z-score) based on these five variables.This section briefly describes how these measures are calculated. More details on the construction of these measures are provided in the Appendix.

Maxret: Bali, Cakici, and Whitelaw (2011) document a significant and negative relation between the maximum daily return over the previous month and the returns in the future. They also show that firms with larger maximum daily returns have higher return skewness. It is conjectured that the negative relation between the maximum daily return and future returns is due to investors' preference for lottery-like stocks. Following their study, we use each stock's maximum daily return (Maxret) as our first measure of lottery feature.

Skewexp: Boyer, Mitton, and Vorkink (2010) estimate a cross-sectional model of expected idiosyncratic skewness and find that it negatively predicts future returns. We use the expected idiosyncratic skewness estimated from their model (model 6 of Table 2 on page 179) as our second measure. Following their estimation, this measure starts from 1988.

Prc: Stocks with low prices attract gamblers because they create an illusion of more potential for future price increase, so we use each stock's closing price as our third measure of the lottery feature. Since low-price stocks are lottery-like assets, so we take a nonessential transformation of stock prices in our empirical tests to be consistent with other proxies, i.e., $Prc = -log(1 + \text{Price})$.

Jackpotp: Conrad, Kapadia, and Xing (2014) show that stocks with a high predicted probability of extremely large payoffs earn abnormally low subsequent returns. Their finding suggests that investors prefer lottery-like payoffs which are positively skewed. Thus, we use the predicted probability of jackpot (log returns greater than 100% over the next year) which is estimated from their baseline model (Panel A of Table 3 on page 461) as our fourth measure.

Ivol: Stocks with high idiosyncratic volatility are attractive to investors with gambling preferences because the high volatility creates the misconception of a high probability to realize high returns. Following Ang, Hodrick, Xing, and Zhang (2006), we compute idiosyncratic volatility (Ivol) as the standard deviation of daily residual returns relative to Fama and French (1993) three-factor model, and use it as our fifth measure of the lottery feature.

Z-score: Z-score is a monthly composite lottery measure calculated as the average of the individual z-scores of the previous five lottery measures: Maxret, Skewexp, Prc, Jackpotp, and Ivol. Each month for each stock, each one of the five lottery measures is first converted into its rank and then standardized to obtain its z-score. We require a minimum of three nonmissing lottery measures out of five to compute this measure.

2.3 Analyst Forecast Dispersion

The analyst forecast dispersion (DISP) is measured by the standard deviation of all valid forecasts of next quarter's EPS during the period of 90 days prior to the announcement date and ending 10 days prior to the announcement date, divided by the absolute value of the mean forecast during the same period.[11] We remove the stale forecasts that were stopped or excluded from the I/B/E/S detail history dataset to calculate this measure.

2.4 Retail Trade Imbalance

To measure retail trade imbalance (RIMB), we follow Hvidkjaer (2006) and use the imbalance inferred from the transaction data from ISSM and TAQ. We only include NYSE and AMEX common stocks from 1983 to 2000. We apply the standard filters and delete trades and quotes with irregular terms and those with likely erroneous prices.

The RIMB is computed in two steps.[12] In the first step, all eligible trades are classified as small, medium or large trades using a variation of the Lee (1992) firm-specific dollar-based

[11] We follow previous literature in using a 90-day window (e.g. Mendenhall (2004), Livnat and Mendenhall (2006)), but our results are not sensitive to this choice. We repeat our tests using forecasts during the 45-day period, 30-day period, and 60-day period prior to the announcement dates, and obtain similar results. All these results are available upon request.

[12] See Hvidkjaer (2006) for more details on the construction of this measure.

trade-size proxy. Each month, we form five portfolios based on firm size at the end of the previous month and then use the size-quintile-specific dollar value below as the breakpoints to identify small, medium or large trades:

Firm-size quintile	Small	2	3	4	Large
Small trade cut-off, in $	3400	4800	7300	10,300	16,400
Large trade cut-off, in $	6800	9600	14,600	20,600	32,800

All trades are further classified as either buy-initiated or sell-initiated based on the tick and the trades rule according to the Lee and Ready (1991) algorithm. A trade is sell-initiated if it is executed at a price below the quote midpoint, and is buy-initiated if it is executed at a price above the quote midpoint. If a trade is executed at the quote midpoint, we use the tick rule: it's sell-initiated if the trade price is below the last executed trade price; it's buy-initiated if the trade price is above the last executed trade price. This procedure classifies all eligible trades into one of six categories: buy-initiated small trades, sell-initiated small trades, buy-initiated medium trades, sell-initiated medium trades, buy-initiated large trades, and sell-initiated large trades. In the second step, for each stock on each day, we compute its retail trade imbalance as the difference between the buy-initiated and sell-initiated small-trade volume divided by the sum of the buy-initiated and sell-initiated small-trade volume: $RIMB = (\text{BUYVOL} - \text{SELLVOL})/(\text{BUYVOL} + \text{SELLVOL})$, where BUYVOL and SELLVOL are the daily buy-initiated and sell-initiated small-trade volume of this stock, respectively. We then take the average of the daily trade imbalance during the (-10,-6) and (-5,-1) event windows, with day 0 referring to the earnings announcement date. Lastly, to capture the change in the sentiment among retail investors before the earnings announcements, we compute the pre-event change as the (-5,-1) RIMB minus (-10,-6) RIMB, normalized by the absolute value of the (-5,-1) RIMB.

2.5 Option Volume

Our option data is from OptionMetrics starting from 1996. Out-of-the-money (OTM) call options are particularly attractive to investors with a gambling preference because the highly skewed payoffs make them like lottery-like assets. If investors are more likely to gamble before earnings announcements, then they might tend to trade more OTM calls than during other periods as well. To capture this sentiment, we use the at-the-money (ATM) call options of the same stock as a benchmark to measure whether investors are more interested in the OTM calls before the announcements. If investors show a stronger gambling preference before the announcements, the daily option volume spread between the adjusted daily volume of OTM and ATM calls should increase during the pre-event window. To compute the adjusted daily volume, we start from all short-term ATM and OTM call options expiring in the following month. An option is defined as ATM if its strike price to stock price ratio is between 0.975 and 1.025. If its strike price to stock price ratio is greater than 1.05, then the option is defined as OTM. We remove options with nonstandard settlement, options that violate basic arbitrage conditions, and options with zero open interest, missing bid or offer prices. After applying these filters, for each stock at each day, we aggregate the trading volume for all its valid OTM and ATM short-term calls, respectively. The adjusted volume is then computed as the percentage change of daily volume from its past 3-month moving average to remove the upward time trend of the trading volume. Lastly, we average the adjusted volume across all stocks for each event day.

2.6 Religious Characteristics

Our main religion proxy is the Catholic-Protestant ratio (CPRATIO) as defined in Kumar et al. (2011). Glenmary Research center collects detailed county-level data on the number of churches and the number of adherents of each church for the years 1971, 1980, 1990, 2000, and 2010, and publishes the data in "Churches and Church Membership" files in the American Religion Data Archive (ARDA). We follow previous literature (e.g., Hilary and Hui (2009), Kumar et al. (2011)) to linearly interpolate the data in the intermediate years. We further merge this religion variable with the firm headquarter location data from Compustat and use it as the firm-level CPRATIO.

2.7 Aggregate Mutual Fund Flow and Hedge Fund Flow

We follow Akbas, Armstrong, Sorescu, and Subrahmanyam (2015) to construct monthly aggregate mutual fund flow (MFFLOW) and hedge fund flow (HFFLOW). The monthly aggregate mutual fund flow is defined as: $MFFLOW_t = \frac{\sum_{i=1}^{N}[TNA_{i,t} - TNA_{i,t-1}(1+MRET_{i,t})]}{\sum_{i=1}^{N} TNA_{i,t-1}}$, where $TNA_{i,t}$ is the total net assets of mutual fund i in month t, $MRET_{i,t}$ is the monthly return of mutual fund i in month t, net of fees. We only include mutual funds with a code of equity objective, and require a fund to have non-missing values for all variables in the MFFLOW equation. Similarly, the monthly aggregate hedge fund flow is defined as: $HFFLOW_t = \frac{\sum_{i=1}^{N}[TNA_{i,t} - TNA_{i,t-1}(1+HRET_{i,t})]}{\sum_{i=1}^{N} TNA_{i,t-1}}$, where $TNA_{i,t}$ is the total net assets of hedge fund i in month t, $HRET_{i,t}$ is the monthly return of hedge fund i in month t, net of fees. Our hedge fund sample starts from 1994 and includes both active and dead funds to minimize survivorship bias. We apply several filters on the hedge fund database. We keep only funds whose returns are reported on a monthly basis and denominated in US dollars. We further exclude funds with main strategy as fixed income arbitrage, managed futures, or emerging markets. Lastly, we delete observations with non-missing values for all variables in the HFFLOW equation. After we obtain monthly MFFLOW and HFFLOW, we further compute quarterly MFFLOW and HFFLOW as the sum of monthly MFFLOW and HFFLOW within a quarter, respectively.

2.8 Summary Statistics

Table 1 presents summary statistics. There are a total of 643,729 quarterly earnings announcements in our sample. $EXRET(-1,+1)$, $EXRET(-5,-1)$, and $EXRET(+1,+5)$, are the buy-and-hold excess returns for the (-1,+1), (-5,-1), and (+1,+5) earnings announcements window periods, respectively, with day 0 referring to the earnings announcement date. The excess return is the difference between the stock return and the return of the value-weighted CRSP index. Firm size (ME) is calculated as price multiplied by the number of shares outstanding, and market-to-book (MB) ratio is ME divided by book value of common stock, both measured at the end of the prior fiscal quarter. Momentum ($MOM(-12,-1)$) is calculated as cumulative stock returns over the past year skipping one month. Turnover is calculated as monthly trading volume divided by the number of shares outstanding. To address the issue of double counting of volume for NASDAQ stocks, we follow Anderson and Dyl (2005) and scale down the volume of NASDAQ stocks by 50% before 1997 and 38% after 1997 to make it roughly comparable to the volume on the NYSE.

3 Pre-event and Post-event Returns

3.1 Portfolio Sorts

In this section, we present our main results that excess returns for lottery-like stocks are significantly higher than non-lottery stocks before earnings announcements, with the opposite pattern holding after earnings announcements. Each quarter, firms with earnings announcements in that quarter are sorted into five portfolios based on each one of the six lottery proxies from the month prior to earnings announcements. If announcement dates are in the first 10 trading days of a month, we lag one more month for the proxies. [13] We calculate equal-weighted excess returns of these lottery portfolios during the (-5,-1) pre-event period and the (+1,+5) post-event period.[14] The t-statistics are calculated based on the heteroskedasticity-consistent standard errors of White (1980).

Panel A.1 of Table 2 reports the results for the pre-event period, and Panel B.1 reports the results for the post-event period. A striking pattern appears: the top quintile lottery portfolio significantly outperforms the bottom quintile before the events, while the opposite pattern appears after the events. Take Maxret as an example. During the (-5,-1) pre-event window, firms in the top Maxret quintile portfolio earn a return of 34 basis points higher than the bottom quintile portfolio with the t-stat equal to 3.46. In other words, the lottery anomaly is completely inverted during this period. In sharp contrast, during the (+1,+5) post-event window, firms in the top Maxret quintile portfolio earn a return of 76 basis points less than the bottom quintile portfolio with the t-stat equal to -7.34.

The other five proxies display similar patterns. In particular, during the pre-event window, the lottery spread is 0.41%, 0.54%, 0.57%, 0.41%, 0.52% for Skewexp, Prc, Jackpotp, Ivol, and Z-score, respectively, indicating that lottery-like stocks significantly outperform non-lottery stocks before earnings announcements. On the other hand, during the post-event window, the lottery spread is -0.70%, -0.57%, -0.65%, -0.77%, -0.80% for Skewexp, Prc, Jackpotp, Ivol, and Z-score, respectively, suggesting that lottery-like stocks significantly underperform non-lottery stocks after earnings announcements. Since many firms report earnings after the market closes, and for these firms, day 0 is not the effective announcement day but the trading day before the earnings announcement.[15] As a result, to obtain a clean measure of post-event performance, we focus on the (+1,+5) post-event window. In the robustness checks section, we use an alternative definition of earnings announcement date based on the day of highest relative trading volume following Engelberg, McLean, and Pontiff

[13]We skip 10 days prior to the earnings announcement date to avoid any look-ahead bias. For example, GM released its 2007 third quarter earnings on Nov. 7, 2007; 10 days before this event was Oct. 24, 2007. To make sure that all the information is publicly available and to avoid any market microstructure complexity, we use proxies from the end of September of 2007 in our portfolio analysis.

[14]For quarterly earnings announcements that firms make on a regular basis, firms are required by law to announce the conference call a reasonable period of time ahead. Thus, most firms (about 90%) announce their earnings announcement schedule at least 6 days ahead (see, e.g., Boulland and Dessaint (2014)).

[15]For example, deHaan, Shevlin, and Thornock (2015) show that almost 50% of earnings announcements are made after trading hours during their sample period of 2000-2011.

(2018), and show that our results remain quantitatively similar.[16] Further, in untabulated tests, we find similar results if we use (0, +5) as our post-event window or (-5, 0) as our pre-event window.

Further, to make sure that the patterns we discovered are specific to earnings announcements, rather than a general phenomenon for any date, we compare the announcement period returns to the non-announcement period using a placebo test based on "pseudo-event" dates. In particular, we repeat our portfolio analysis in Panel A.1 and Panel B.1 using randomly selected non-announcement dates. Following So and Wang (2015), pseudo-announcement dates are chosen from a baseline period relative to the actual announcement dates by subtracting a randomly selected number of days that is drawn from a uniform distribution from 10 to 40 days. We skip 10 days from the actual announcement dates to avoid the scenario that the post-event period of the pseudo-announcement dates overlaps with the pre-event period of the actual-announcement dates. Panel A.2 and Panel B.2 report the results for these 'pseudo-announcement" portfolios. Lottery-like stocks generally earn similar returns to non-lottery stocks. More importantly, Panel A.3 and Panel B.3 compare the "actual-announcement" and 'pseudo-announcement" portfolios and report their differences. All the difference-in-differences are significant with the right sign during both pre-event and post-event periods, in both the statistical and economical sense.

Figure 1 plots the difference of cumulative buy-and-hold excess returns between top and bottom quintile portfolios based on lottery proxies over the (-5,+5) 11 trading days centered around the earnings announcement dates. In particular, we calculate equal-weighted average buy-and-hold excess returns accumulated starting from day -5. We plot the difference of the average returns between the top and the bottom quintile lottery portfolios. For all six lottery proxies, the returns of these hedge portfolios start to increase 5 days prior to the event date and then decrease immediately after the event, with the biggest drop happening on the date right after the event. Further, a similar pattern holds if we use the (-10,+10) 21 trading days event window as shown in Figure 2. In sum, we provide information on when the overvaluation of lottery-like stocks occurs in the first place, while most prior studies focus on the subsequent reversals for lottery-like stocks.

We have documented an inverted-V shaped cumulative return spread based on lottery proxies before and after earnings announcements in Figure 1. One might think that the

[16] As another robustness check, in untabulated tests, we repeat the analysis using the earlier of the IBES earnings announcement and Compustat earnings announcement dates as the definition of earnings announcement date, following DellaVigna and Pollet (2009). Our results remain similar, and are available upon request.

more intense speculative trading behavior may also hold for other anomaly characteristics, and thus there is nothing special about our results for the inverted-V shaped cumulative lottery spreads. Thus, for comparison, we also perform the same exercise for a set of other anomaly-related characteristics. Probably the most well-known anomalies are value and momentum. Recently, profitability and investment have also attracted a lot of attention. In particular, Novy-Marx (2013), Fama and French (2015, 2016), and Hou, Xue, and Zhang (2015) show that new factor models with additional factors related to profitability and investment can account for a large set of asset pricing anomalies. Thus, we repeat our exercise for value, momentum, profitability, and investment, and plot the cumulative anomaly return spreads around the earnings announcements in Figure 3. First, the return spreads are more pronounced around the earning announcements than in other periods, a finding consistent with La Porta et al (1997) and Engelberg, McLean, and Pontiff (2018). More importantly, the cumulative return spreads based on book-to-market, past returns, profitability and the opposite of investment over assets increase *both* before and after earnings announcements. It is worth noting that the shape for cumulative return spread in Figure 3 is monotonically increasing, whereas for lottery characteristics, an inverted-V shape obtains. This contrast highlights the unique role of speculation ahead of earnings announcements for our lottery-related characteristics.

3.2 Fama-MacBeth Regressions

The portfolio approach in the previous section is simple and intuitive, but it cannot explicitly control for other variables that may influence returns. To control for other firm characteristics, we perform a series of Fama and MacBeth (1973) cross-sectional regressions.

In all of the Fama-MacBeth regressions below, we regress event-window excess returns on a list of lagged traditional variables, such as firm size, book-to-market, and past returns. Independent variables (except for returns) are winsorized at their cross-sectional 1st and 99th percentiles, and t-statistics are calculated based on the heteroskedasticity-consistent standard errors of White (1980). Panel A of Table 3 reports the regressions during the (-5,-1) pre-event window. Consistent with our prediction, the lottery proxy is positive and significant for all six lottery proxies. Further, the regressions during the (+1,+5) post-event window reported in Panel B show the negative and significant predictive power of all lottery measures as well. In particular, when the composite z-score increases by one standard deviation, the pre-event 5-day return tends to increase by 0.188%, and the post-event 5-day return tends to decrease by an even larger amount of 0.396%.

In sum, the evidence based on both the portfolio sorting approach and Fama-MacBeth regressions is consistent with the notion that investors are especially attracted to lottery-like stocks before earnings announcements, which generates positive lottery spreads that are in the opposite direction from the traditional lottery anomalies.

4 Inspecting the Mechanisms

In this section, we provide further evidence of inventors' gambling behavior before earnings announcements. In particular, we will present results controlling for differences of opinion as well as results from the retail trade imbalance and the trading behavior on the options market.

4.1 Differences of Opinion

Berkman et al. (2009) also argue that speculative trading tends to increase prior to earnings announcements. In addition, the Miller (1977) model suggests that stock prices are likely to reflect optimists' opinions due to short-sale impediments. Consequently, the net effect of intensified speculative trading on prices is expected to be positive and should lead to increasing overvaluation just ahead of earnings announcements. Moreover, because investors who are more optimistic are more likely to take such speculative positions, the increase in overvaluation should be larger for stocks with higher levels of differences of opinion. Based on these arguments, Berkman et al. (2009) hypothesize that the price run-up during the days leading up to earnings announcements for stocks with large differences of opinion should be greater than those with small differences of opinion. Indeed, Berkman et al. (2009) find supportive empirical evidence.

Lottery-like stocks might have more information uncertainty, which induces larger differences of opinion among investors. Thus, to make sure that our results are not driven by the potential correlation between our proxies for the lottery feature and differences of opinion, we directly control for differences of opinion in Fama-MacBeth regressions. We adopt two common proxies for differences of opinion: analyst forecast dispersion and turnover. Table 4 reports the results. Panel A adds analyst forecast dispersions before the announcements and Panel B adds turnover in the previous month into the Fama-MacBeth regressions. In the pre-event regressions, the lottery proxy is still positive and significant for all six proxies, controlling for either analyst forecast dispersion or turnover. More interestingly, the dispersion is not significant in any of the six pre-event regressions, suggesting that our results cannot be explained by the differences of opinion story. Actually, our results indicate that once lottery proxies are controlled, the level of differences of opinion is not positively related to returns ahead of the earnings announcements, suggesting that the lottery effect might play a role in the findings in Berkman et al (2009).[17]

Lastly, in untabulated analysis, we also replace the level of differences of opinion with changes in differences of opinion ahead of the earnings announcements.[18] We find that our results remain quantitatively similar.[19] In addition, since stocks with analyst coverage tend to be larger, the evidence in Table 4 also indicates that our results hold for relatively large stocks and are not completely driven by small stocks.

4.2 Evidence from Retail Trade Imbalance

Lottery preferences, like other behavioral biases, tend to be more prominent among individual investors (see, e.g., Kumar (2009)). In addition, earnings announcement events tend to grab retail investors' attention. Indeed, Drake, Roulstone, and Thornock (2012) show that investor attention measured by abnormal Google search is increased significantly ahead of earnings announcements. Thus, the attention-driven demand for lotteries could be increased

[17]The main focus of Berkman et al. (2009) is on the more pronounced underperformance of stocks with high levels of differences of opinion around the earnings announcements due to reduction in disagreement, rather than the outperformance of these stocks ahead of earnings announcements. Thus, even if the lottery effect plays a significant role in their finding on the outperformance of high dispersion stocks ahead of earnings announcements, it does not weaken the main argument and conclusion in Berkman et al. (2009).

[18]The reason that we control for changes in differences of opinion is the following. Differences of opinion might be more severe before earnings announcements because of the high uncertainty during the pre-event period. After the announcements, the uncertainty will be partly resolved as will be the differences of opinion. Furthermore, this effect might be more pronounced for firms with large differences of opinion. In other words, the change in the differences of opinion among investors has a similar time trend as the return pattern we documented in the previous section in Figure 1. Coupled with short-sale constraints, this pattern on differences of opinion could potentially explain our results.

[19]In another untabulated analysis, we also control for the extrapolated returns measured by the weighted average of announcement returns from the firm's past eight quarterly earnings announcements as in Ertan, Karolyi, Kelly, and Stoumbos (2017). Ertan et al. (2017) find a similar inverted V-shape price pattern for stocks with high recent earnings surprises. These stocks experience price increase before earnings announcements and price decrease afterwards, due to investors' overextrapolation of earnings announcement performance. To control for the possible correlation between lottery proxies and past announcement returns, we add past announcement returns into the Fama-MacBeth regressions, and our results still hold.

ahead of earnings announcements. Consequently, we expect to see more trading initiated by retail investors before earnings announcements, especially among lottery-like stocks. Table 5 compares the change in retail trade imbalance of lottery-like and non-lottery stocks prior to the announcements. As shown in Panel A, there is indeed an increase in retail trade imbalance for an average stock ahead of earnings announcements. Moreover, the increase in retail trade imbalance is generally significantly larger among lottery-like stocks than among non-lottery stocks.[20]

The more pronounced increases in retail trade imbalance on lottery-like stocks is likely to lead to price increases of those stocks. When there is an imbalance between buy and sell orders, market markers may absorb the order imbalance by serving as the trade counterparty. However, market makers may demand greater compensation for incurring inventory risks due to the greater anticipated volatility associated with the information event (see, e.g., Nagel (2012) and So and Wang (2015)). In addition, as discussed in the introduction, arbitrage forces should also be more limited ahead of earnings announcements due to greater uncertainty. Taken together, it implies a greater price run-up for lottery-like stocks ahead of earnings announcements, consistent with our main findings in Table 2.

In light of the above discussion, we also study how retail trade imbalance affects returns ahead earnings announcements. In Panel B, we use the regression approach where we include the (-5,-1) RIMB and its interaction with lottery proxies along with all other controls in the Fama-MacBeth regressions framework used by the previous section (i.e., Table 4, Panel B). All the interaction terms between retail trade imbalance and lottery proxies appear to be positive and significant, indicating that an increased retail investor interest before the announcements tends to amplify the positive lottery spread before the announcements. Lastly, in untabulated tests, we use a short sample of detailed individual transaction data from Barber and Odean (2000, 2001, 2002),[21] and also find some preliminary evidence that individual investors are more likely to buy lottery-like stocks before earnings announcements.

[20]In untabulated tests, we also conduct the same analysis for investors' visits to company filings at the SEC Edgar website. We find a similar pattern that the lottery-like stocks experience significant increases in investors' requests during the pre-event period.

[21]We thank Terrance Odean for sharing the data with us.

4.3 Evidence from the Option Markets

In addition to the direct evidence from investors' trading behavior on the stock market, we also examine whether the gambling preference exists in the options market and whether it is intensified ahead of earnings announcements. OTM calls are a natural candidate for gambling because they are cheap and have highly skewed payoffs. Therefore, if investors have a stronger demand for lottery before the earnings announcements, they would be more likely to buy short-term OTM calls prior to the event. We use the ATM calls on the same stock as the benchmark, and plot the dynamics of the OTM call trading volume relative to the ATM call trading volume during the (-5,+5) event window in Figure 4. As expected, the relative trading volume starts to increase from 5 days prior to the event, peaks at the event date, and then sharply drops immediately after the event. This pre-event increase pattern echoes that of the retail trade imbalance of the lottery-like stocks in the stock market.

In sum, the results from investors' trading behavior on the stock market and the options market provide further support for our hypothesis on investors' amplified demand for lottery ahead of earnings announcements.

4.4 Evidence from Religious Beliefs in Gambling Propensity

In this subsection, we examine the role of religious beliefs in gambling propensity. Kumar et al. (2011) finds that there is geographic variation in religion-induced gambling preference, and the lottery-stock premium is larger when a firm is located in a region with high concentrations of Catholics relative to Protestants. Compared to the more tolerant gambling views of Catholic churches, many Protestant churches have strong moral opposition to gambling and consider it as a sinful activity.

Following their logic, if the speculative trading is due to lottery-like preferences, we expect the effect to be stronger for firms in high CPRATIO regions as well. To test this conjecture, we add the log of CPRATIO and its interaction with our lottery proxies into the Fama-MacBeth regressions. Table 6 reports the results. Consistent with our prediction, the interaction terms are all positive in the pre-event regressions and the sign flips for four out of six proxies in the post-event regressions. That is, the inverted-V shaped pattern on cumulative return spreads is more pronounced among firms in the regions with stronger gambling propensity.

4.5 Additional Robustness Checks

In this section, we report the results of several additional robustness tests.

First, we conduct a subsample analysis based on institutional ownership. Compared to individual investors, institutional investors should be less subject to behavioral biases such as lottery preference. Therefore, we perform a double-sorting portfolio analysis. Stocks are first divided into 2 groups bases on the institutional ownership (IO) at the end of the previous quarter, and then within each group, stocks are further divided into 5 portfolios based on each one of the six lottery proxies from the month prior to the announcement date. If the announcement date is in the first ten trading days of a month, we lag one more month for the proxies. IO is defined as the percent of shares held by institutional investors as reported in Thomson Financial 13F database. Table 7 reports the lottery spread within these subsamples as well as their differences during the pre-event and post-event period. Consistent with our conjecture, during the pre-event period, the lottery spreads are generally bigger within the bottom 50% IO subsample, and the difference between top and bottom IO group is significant for four of the six proxies. A similar pattern also appears during the post-event period, where the underperformance of lottery-like stocks is more severe among the low IO subsample, with the difference-in-differences significant for all six proxies.

Second, we examine the international data to see whether the results we documented are an international phenomenon. We repeat the analysis in Table 2 for other non-US G7 countries. For each country, we construct a composite z-score based on three lottery proxies, Maxret, Prc, and IVOL.[22] Table 8 shows that the same pattern emerges for most G7 countries. In particular, the return spread between lottery-like and non-lottery stocks before earnings announcements are 0.64%, 1.20%, 0.65%, 0.36%, -0.47%, 0.02% for Canada, Germany, France, UK, Italy, and Japan, respectively. In contrast, the return spread between lottery-like and non-lottery stocks after earnings announcements are -0.68%, -1.12%, -0.57%, -1.00%, -0.84%, and -1.33% in these countries. Further, we plot the difference of cumulative buy-and-hold excess returns between top and bottom quintile portfolios based on the composite z-score over the (-5,+5) 11 trading days centered around earnings announcements for non-US G7 countries in Figure 5. A similar pattern to our US Figure 1 emerges: except

[22] The data to construct the other two lottery proxies are limited, thus we only use these three easy-to-calculate proxies to compute our composite z-score for international stocks. To calculate IVOL for other G7 countries, we first construct a local market three-factor model following Gao, Parsons, and Shen (2015), and then IVOL is the standard deviation of residuals from daily three-factor regressions. More details on international data are provided in the Appendix.

for Italy, the returns of these hedge portfolios start to increase 5 days prior to the event date and then decrease immediately after the event, with the biggest drop happening on the day right after the event.[23]

Our third robustness test examines the realized return skewness of lottery-like and non-lottery stocks during the event window. Lottery-like stocks tend to have higher skewness than non-lottery stocks on average. More importantly, investors might believe that the differences in skewness between lottery-like and non-lottery stocks are particularly large during the earnings announcement periods as compared to other periods. Thus, investors prefer lottery-like stocks more strongly before earnings announcements. To test this prediction, we calculate the realized skewness between top and bottom quintile lottery portfolios during both the actual-event period and the pseudo-event period, and compare the difference-in-differences. Panel A of Table 9 reports the results. As expected, the (-1,+1) event-window returns of lottery-like stocks have higher skewness than non-lottery stocks on average. In addition, lottery-like stocks have much higher realized skewness during the event window than during other times, while the skewness for non-lottery stocks is similar across the event window and the non-event window. More important, the difference-in-differences of skewness are higher during event periods than other periods for all six proxies. Further, apart from return skewness, we also examine the realized skewness of earnings surprises on announcement dates. Panel B of Table 9 reports the results. For all six lottery proxies, the realized skewness of earnings surprises is also much higher among lottery-like stocks than non-lottery stocks.

Our fourth robustness test includes the earnings announcement date in the post-event window. Since many firms report earnings after the market closes, so our tests so far exclude day 0 from the post-event window. In untabulated analysis, we confirm that the pre-event effect remains similar if we choose (-5, 0) as our pre-event window and the post-event reversal effect also remains similar if we choose (0,+5) as our post-event window. These results are omitted from the paper and available upon request. Moreover, we also adopt an alternative definition of earnings announcement dates by following Engelberg, McLean, and Pontiff (2018). For each firm, we first compute its daily trading volume scaled by market trading volume for each day before, the day of, and the day after the reported earnings announcement

[23] U.K. shows a different pattern from other countries at day 0 because of its different earnings report schedule. Unlike US firms which typically report either before the start of trading or after the closing bell, most U.K. companies report their earnings at 7am London time. In addition, for Italy, the stock market participation of individual investor is quite low relative to other G7 countries probably due to the weak corporate governance, see, e.g., Maher and Andersson (2000), Guiso, Sapienza, and Zingales (2008). It is possible that due to lower retail investor participation, the effect in Italy is absent in our sample.

date from Compustat quarterly database. The highest relative trading volume day among these three days is treated as the earnings announcement day. Table 10 reports the portfolio results based on this alternative definition. The results are largely the same as before.

Our fifth robustness test investigates the lottery return spread around earnings announcements among the subsample of early, on-time, and late announcers. Some firms make earnings announcements earlier than the expected dates, while others are later than the expected dates. Earlier studies find that early announcers tend to have good news while late announcers tend to have bad news (e.g., Givoly and Palmon (1982), Chambers and Penman (1984), Bagnoli, Kross, and Watts (2002) and Johnson and So (2016)). When some investors anticipate good news, they might have an even stronger demand for lottery-like stocks, and thus lead to a higher lottery return spread. Furthermore, advancers tend to receive more positive media attention than delayers. Thus, due to greater attention ahead of earnings announcements, the lottery return spreads might be larger as well among earlier announcers.

To perform a formal test, we repeat the exercise in Table 2 within the subsample of early, on-time, and late announcers relative to the expected earnings announcement dates. Following So and Wang (2015), expected earnings announcement dates are calculated by adding the historical reporting lag to the current fiscal quarter end. The historical reporting lag is the median number of trading days between a firm's fiscal quarter end and its actual announcement date for the same fiscal quarter over the previous ten years. Early, on-time, and late announcers are firms whose actual announcement dates are more than one day before, within one day, and more than one day after the expected earnings announcement dates, respectively.

We report the time series average of excess returns of these lottery portfolios and the differences between top and bottom quintile portfolios around the earnings announcement window within the subsample of early, on-time, and late announcers relative to the expected earnings announcement dates. The results in Table 11 indicate that the positive lottery return spreads are largest among early announcers, moderate among on-time announcers, and the weakest among late announcers.This evidence is consistent with the fact that early announcers tend to have good news and more positive media coverage while late announcers tend to have bad news and less positive media attention. Anticipating the good news (at least by some investors), the stronger demand for lottery-like stocks might be amplified even further, thus leading to a larger lottery return spread ahead of earning news among earlier announcers. On the other hand, for late announcers, in anticipation of bad news, investors may shy away from the lottery-like stocks, and thus we do not observe a positive lottery return spread before earnings announcements among these late announcers.

In untabulated analysis, we also repeat the exercise in Table 11 among the subsample of firms with ex post good earnings news, ex post no earning surprise, and ex post bad earnings news. If part of the earnings news is leaked or anticipated by some investors, then we should observe a similar pattern: the lottery return spreads ahead of earnings news should be strongest among firms with ex post good news, moderate among firms with no surprise, and weakest among firms with ex post bad news. Indeed, our untabulated analysis confirms this conjecture.

As our last robustness test, Table 12 examines the time series pattern of the our documented inverted-V shape of lottery spreads. Specifically, we run a time series regression of the return spreads between top and bottom lottery quintile portfolios during the event window on contemporaneous aggregate mutual fund flows (MFFLOW) and aggregate hedge fund flows (HFFLOW) at the quarterly frequency. Panel A reports the result during the (-5,-1) pre-event window, and Panel B reports the result during the (+1,+5) post-event window. Consistent with the finding in Akbas et al. (2015) that mutual fund flow is the dumb money, MFFLOW is positively and significantly related to the price run-up of the lottery stocks. The effect of HFFLOW is the opposite, but insignificant, probably reflecting the severe limits of arbitrage before earnings announcements. The effect of MFFLOW on pre-event return is also consistent with Edelen, Ince, and Kadlec (2016) who find that institutional money is generally on the wrong side of return anomalies. For post-event returns, when MFFLOW is high, the post-event return spreads between lottery and non-lottery stocks are smaller, consistent with the view that MFFLOW impedes the correction of mispricing. However, the results for HFFLOW are the opposite, consistent with the view that HFFLOW accelerates the correction of mispricing. These findings are consistent with Akbas et al. (2015) that mutual fund flow is dumb, whereas hedge fund flow is smart.

5 Refined Lottery Strategy

Given our previous findings on the different return patterns of lottery-like stocks before and after earnings announcements, we propose a refined lottery strategy and compare it with the standard lottery strategy in this section.

Since lottery-like stocks underperform non-lottery stocks on average, the standard lottery strategy typically holds a hedge portfolio which buys non-lottery stocks and sells lottery-like stocks. Given our findings in the previous sections that lottery-like stocks actually outperform non-lottery stocks before earnings announcements, we therefore propose a refined lottery strategy of buying lottery-like stocks and selling non-lottery stocks during the (-10,-1) pre-event window, and then reverting to the standard lottery strategy afterwards. To ensure that the strategy is implementable, we only use the pre-event dates in the same month of the actual announcement date. In other words, instead of longing non-lottery stocks and shorting lottery-like stocks during the entire month t after forming lottery portfolios at the end of month $t-1$ as in the standard lottery strategy, for stocks with scheduled earnings announcements in month t, we sell the stock if it belongs to the bottom lottery quintile, or buy the stock if it's in the top lottery quintile, during the (-10,-1) pre-event window. Further, if the earnings announcement date is in the first ten trading days of month t, in which case some dates of the (-10,-1) pre-event window are actually in month $t-1$, we skip these pre-event dates in month $t-1$ and only adopt this reverse strategy for those pre-event dates in month t after the portfolio formation at the end of month $t-1$.

Table 13 reports the value-weighted excess returns and Fama-French four-factor alphas for monthly quintile portfolios under the standard lottery strategy (Panel A) and our refined strategy (Panel B) as well as their differences (Panel C). While the standard lottery strategies achieve a positive and significant alpha for four of six proxies, our new strategies significantly increase these return spreads. Take the composite Z-score as an example. Our new strategy improves the long-short portfolio performance by about 38% by increasing the average monthly Fama-French four-factor alpha from 1.09% to 1.50%, with the t-stat of the difference-in-differences equal to 2.48. In untabulated analysis, we use equally weighted portfolio strategies instead of value-weighted strategies, and we find that the improvement is even more statistically significant. Nonetheless, an important caveat is that in reality the improvement might be much smaller due to higher transaction costs associated with this new strategy.

6 Conclusion

In this paper, we argue that investors' preferences for lottery/gambling are time varying, and are especially strong ahead of earnings news, probably due to lower inventory costs for speculators. Meanwhile, the countervailing arbitrage forces are more limited due to elevated uncertainty leading to the earnings news. Taken together, we expect that there should be positive return spreads between lottery-like assets and non-lottery assets during the days ahead of earnings announcements. Indeed, we document that the return spreads between lottery-like assets and non-lottery assets have opposite patterns before and after earnings announcements. Most prior studies show that lottery-like stocks can be overvalued and focus on the subsequent price reversal of the lottery-like stocks. Thus, our focus on earnings announcements identifies the periods when the overvaluation of the lottery-like stocks occurs, rather than their subsequent corrections as studied by most prior studies.

Our empirical findings are robust across six different proxies that are studied in the literature of lottery-related anomalies. In addition, this inverted-V shaped pattern on lottery return spreads is more pronounced among firms with more retail trade imbalance, with low institutional ownership, and in the regions with stronger gambling propensity. Moreover, we show that the cumulative return spreads based on other anomalies characteristics such as book-to-market, past returns, profitability and the opposite of investment over assets are increasing *both* before and after earnings announcements. Thus, the inverted-V shaped cumulative return spread is unique to lottery-related characteristics. This sharp contrast in the shape of cumulative return spreads highlights the unique role of speculation ahead of earnings announcements for our lottery-related characteristics.

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Figure 1: Event-time lottery portfolio excess returns over 11 trading days

This figure plots the cumulative buy-and-hold hedge portfolio returns (in percentage) during the (-5,+5) event window centered at the earnings announcement date. Each quarter, firms with earnings announcements are divided into five portfolios based on each one of six lottery proxies from the month prior to the announcements. If the earnings announcement date is in the first 10 trading days of a month, we lag one more month and use the lottery proxies from two months prior to the announcements. For each day during the (-5,+5) event window for each portfolio, we calculate the equal-weighted average buy-and-hold excess returns (in excess of the value-weighted return of the CRSP index) accumulated starting from day -5. We plot the difference of the average returns between the top and the bottom quintile lottery portfolios. We consider six lottery proxies: Maxret, Skewexp, Prc, Jackpotp, Ivol, and Z-score. Maxret is the maximum daily return; Skewexp is the expected idiosyncratic skewness from Boyer et al.(2009); Prc is negative log of one plus stock price, i.e., $Prc = -log(1 + \text{Price})$; Jackpotp is the predicted jackpot probability from Conrad et al.(2014); Ivol is idiosyncratic volatility from Ang, Hodrick, Xing, and Zhang (2006); Z-score is a composite Z-score based on the previous five lottery proxies. Detailed variable definitions are described in the Appendix. We exclude stocks with a price less than $1 per share at the end of the month prior to the earnings announcements. The sample period is from 1972 to 2014 except for Skewexp which is from 1988 to 2014.

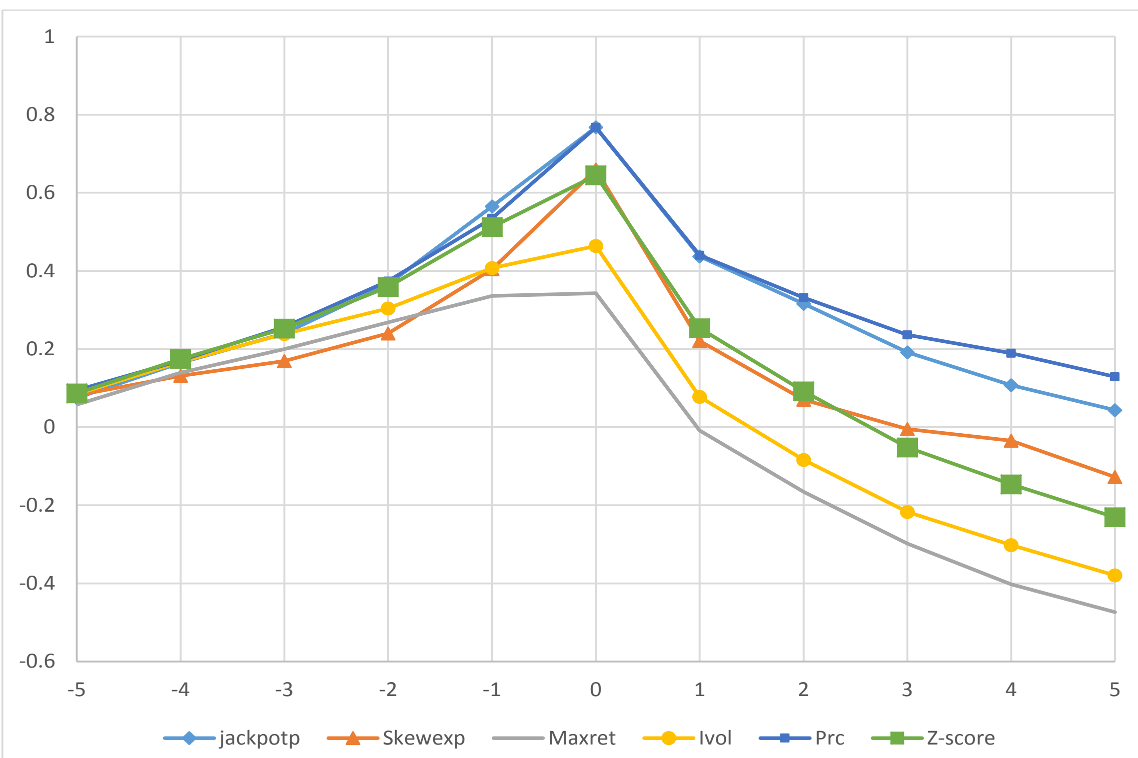

Figure 2: Event-time lottery portfolio excess returns over 21 trading days

This figure plots the cumulative buy-and-hold hedge portfolio returns (in percentage) during the (-10,+10) event window centered at the earnings announcement date. Each quarter, firms with earnings announcements are divided into five portfolios based on each one of six lottery proxies from the month prior to the announcements. If the earnings announcement date is in the first 10 trading days of a month, we lag one more month and use the lottery proxies from two months prior to the announcements. For each day during the (-10,+10) event window for each portfolio, we calculate the equal-weighted average buy-and-hold excess returns (in excess of the value-weighted return of the CRSP index) accumulated starting from day -10. We plot the difference of the average returns between the top and the bottom quintile lottery portfolios. Lottery proxies are defined the same as in Figure 1. We exclude stocks with a price less than \$1 per share at the end of the month prior to the earnings announcements. The sample period is from 1972 to 2014 except for Skewexp which is from 1988 to 2014.

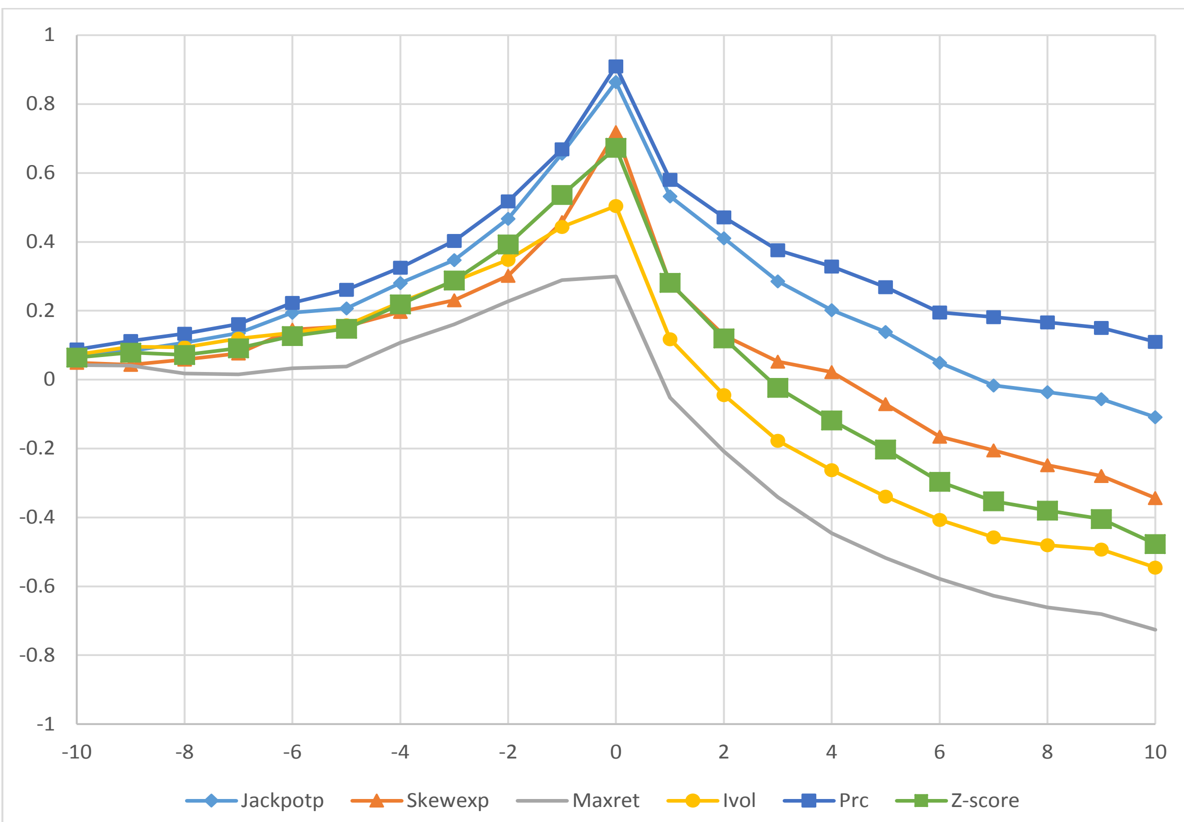

Figure 3: Event-time portfolio excess returns over 11 trading days

This figure plots the cumulative buy-and-hold hedge portfolio returns (in percentage) during the (-5,+5) event window centered at the earnings announcement date. Each quarter, firms with earnings announcements are divided into five portfolios based on each one of four proxies from the month prior to the announcements: Book-to-market equity (B/M), Momentum (MOM), Profitability (ROA), and the opposite of Investment-to-assets (-IA). If the earnings announcement date is in the first 10 trading days of a month, we lag one more month and use the proxies from two months prior to the announcements. For each day during the (-5,+5) event window for each portfolio, we calculate the equal-weighted average buy-and-hold excess returns (in excess of the value-weighted return of the CRSP index) accumulated starting from day -5, and plot the difference of the average returns between the top and the bottom quintile portfolios. BM is the book value of equity divided by market value at the end of the last fiscal year. MOM is the cumulative stock return over the past year skipping one month. ROA is quarterly earnings divided by total assets in the previous quarter. IA is the annual change in total assets divided by total assets in the previous year. We exclude stocks with a price less than $1 per share at the end of the month prior to the earnings announcements. The sample period is from 1972 to 2014.

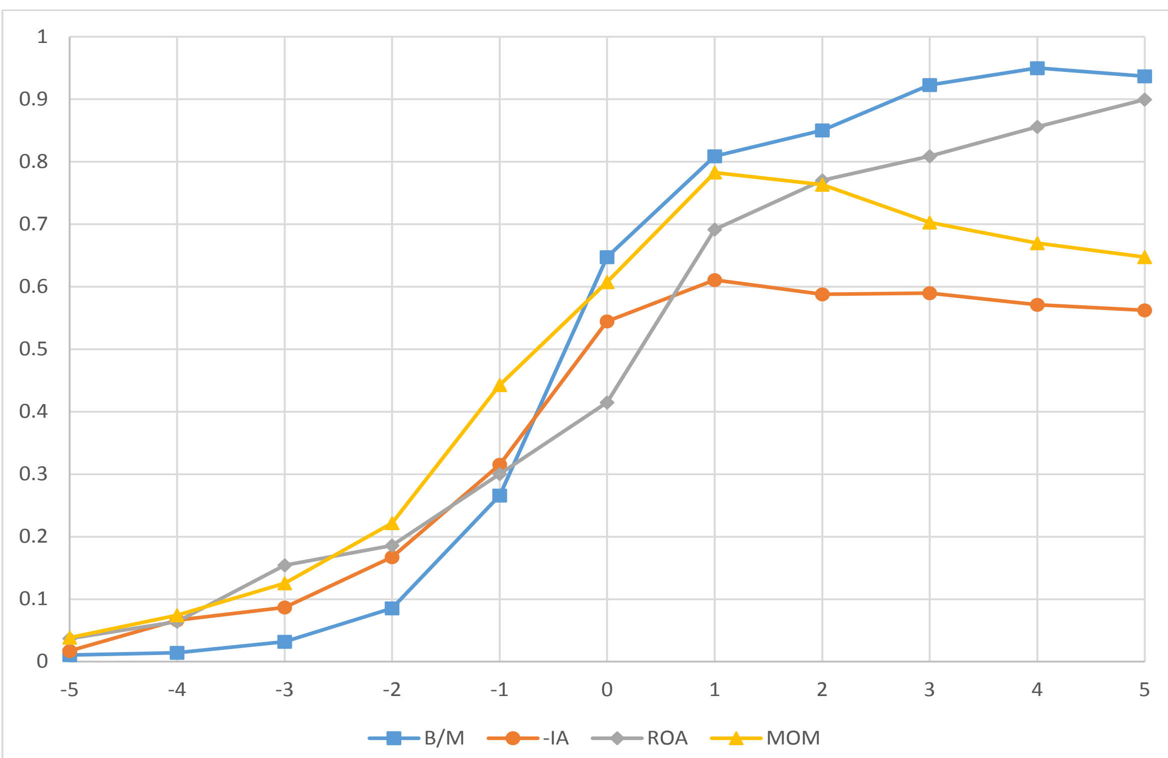

Figure 4: Event-time aggregate call options trading volume spread

This figure plots the daily adjusted volume spread of short-term OTM call options relative to ATM call options during the (-5,+5) event window centered at the earnings announcement date averaged across all stocks. We only use short-term options expiring in the next month. The adjusted volume for OTM (ATM) calls is defined as the difference between the daily OTM (ATM) volume and its 3-month moving average, normalied by its 3-month moving average. The adjusted volume spread is the difference between the adjusted volume of OTM and ATM calls. The sample period is from 1996 to 2014.

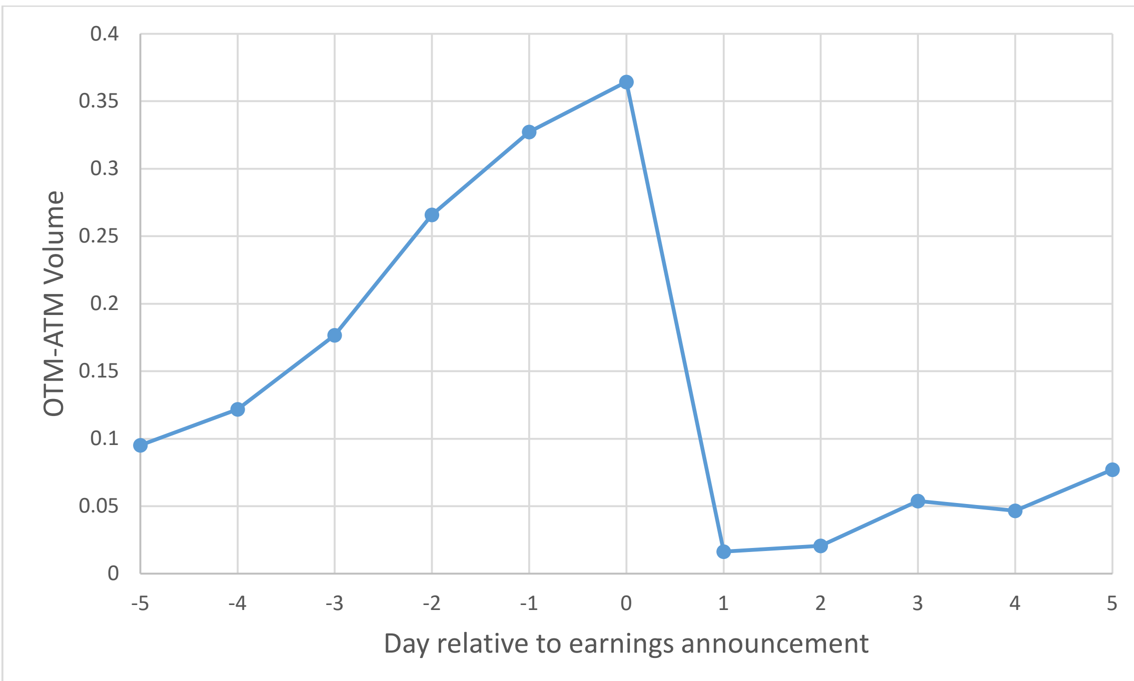

Figure 5: Event-time portfolio excess returns for non-US G7 countries

This figure plots the cumulative buy-and-hold hedge portfolio returns (in percentage) during the (-5,+5) event window centered at the earnings announcement date for non-US G7 countries. Each quarter within each country, firms with earnings announcements are divided into five portfolios based on a composite z-score of three lottery proxies from the month prior to the announcements (Maxret, Prc, and Ivol). If the earnings announcement date is in the first 10 trading days of a month, we lag one more month and use the lottery proxies from two months prior to the announcements. Maxret is the maximum daily return; Prc is negative log of one plus stock price, i.e., $Prc = -log(1 + \text{Price})$; Ivol is idiosyncratic volatility from Ang, Hodrick, Xing, and Zhang (2009). We calculate the equal weighted average buy-and-hold excess returns (in excess of the value-weighted return of the local market portfolio) accumulated starting from day -5. All local currencies are converted to US dollars. We plot the difference of the average returns between the top and the bottom quintile z-score portfolios. Detailed variable definitions are described in the Appendix. The sample period is from September 1999 to December 2014 for Canada, April 2002 to December 2014 for Germany, January 2004 to September 2014 for France, January 1994 to December 2014 for UK, April 2003 to December 2014 for Italy, and October 2001 to December 2014 for Japan.

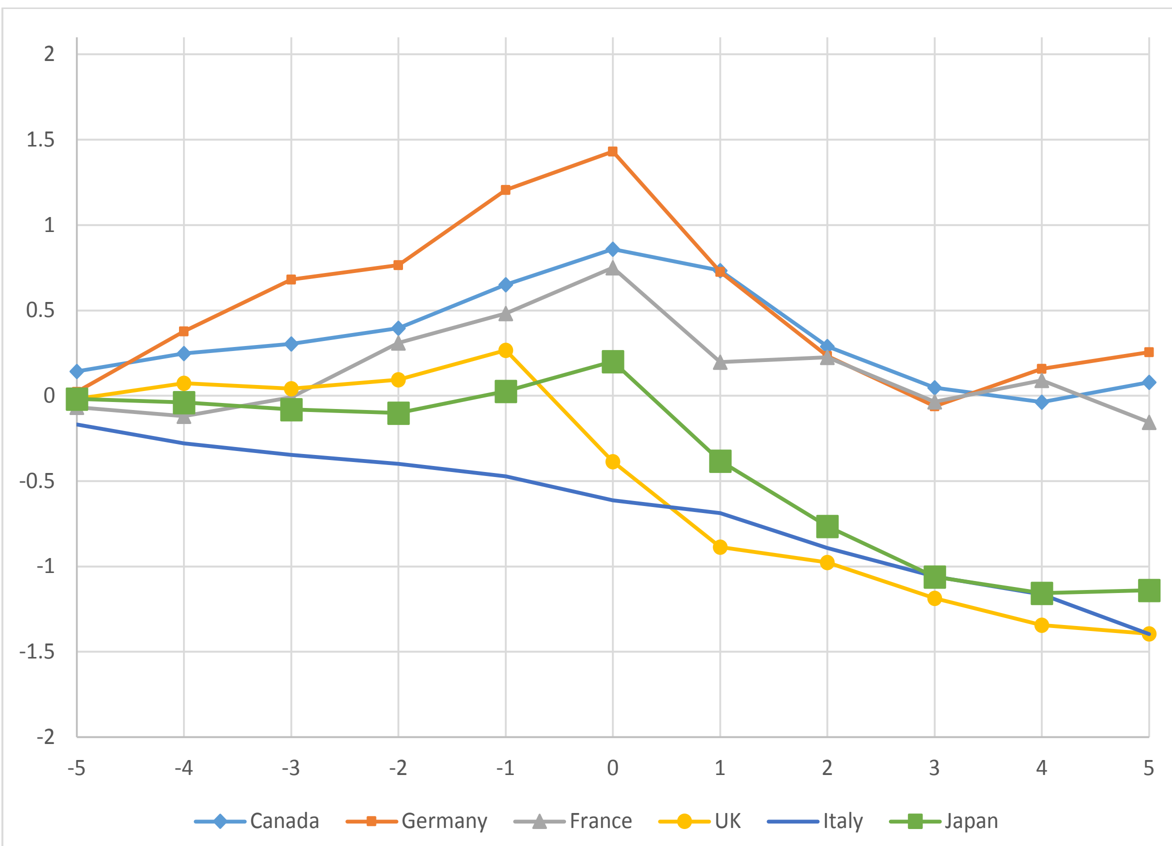

Table 1: Summary Statistics

This table reports the summary statistics for our sample of firm-quarter observations. $EXRET(-1,+1)$, $EXRET(-5,-1)$, and $EXRET(+1,+5)$, are the buy-and-hold excess returns for (-1,+1), (-5,-1), (+1,+5) three relevant earnings announcement window periods, respectively, with day 0 referring to the earnings announcement date. The excess return is the difference between stock return and the return of the value-weighted CRSP index. ME is the market value of equity in millions, and MB is ME divided by the book value of equity, both measured at the end of the prior fiscal quarter. Momentum ($MOM(-12,-1)$) is cumulative stock returns over the past year skipping one month. Turnover is monthly trading volume divided by the number of shares outstanding. To address the issue of double counting of volume for NASDAQ stocks, we follow Anderson and Dyl (2005) and scale down the volume of NASDAQ stocks by 50% before 1997 and 38% after 1997 to make it roughly comparable to the volume on the NYSE. We consider six lottery proxies: Maxret is the maximum daily return, Skewexp is the expected idiosyncratic skewness from Boyer et al.(2009), Price is month-end stock price, Jackpotp is the predicted jackpot probability from Conrad et al.(2014), and Ivol is the standard deviation of daily residual returns relative to the Fama and French (1993) three-factor model from Ang, Hodrick, Xing, and Zhang (2006). Z-score is a composite Z-score based on the previous five lottery proxies. Detailed variable definitions are described in the Appendix. We exclude stocks with a price less than $1 per share at the end of the month prior to the earnings announcements. All continuous variables (except returns) are winsorized cross-sectionally at the 1st and 99th percentiles. The sample period is from 1972 to 2014 except for Skewexp which is from 1988 to 2014. Variables are reported in percentages except for ME, MB, Skewexp, Price, and Z-score.

	Mean	Std	Q1	Median	Q3
EXRET(-1,+1)	0.204	8.708	-3.384	-0.075	3.414
EXRET(-5,-1)	0.331	7.819	-3.128	-0.113	3.093
EXRET(+1,+5)	-0.170	8.973	-3.944	-0.409	3.171
ME	1496.112	5707.589	39.791	151.830	684.693
MB	2.862	4.492	1.026	1.672	2.923
MOM(-12,-1)	0.167	0.733	-0.178	0.067	0.346
Turnover	7.432	10.078	1.631	3.938	9.078
Maxret	6.869	5.865	3.150	5.128	8.499
Skewexp	0.750	0.598	0.332	0.653	1.092
Price	19.505	18.312	6.375	14.375	26.750
Jackpotp	1.818	3.071	0.534	1.052	1.989
Ivol	2.612	1.915	1.303	2.061	3.305
Z-score	-0.059	0.838	-0.764	-0.112	0.612

Table 2: Pre-event and Post-event Portfolio Returns

Each quarter, firms with earnings announcements in that quarter are sorted into five portfolios based on each one of six lottery proxies from the month prior to the announcement date. If the announcement date is in the first ten trading days of a month, we lag one more month for the proxies. We report equal-weighted excess returns of these lottery portfolios, and the differences between top and bottom quintile portfolios during the (-5,-1) pre-event period in Panel A.1 and the (+1,+5) post-event period in Panel B.1, with day 0 referring to the earnings announcement date. Panel A.2 and B.2 present analogous average returns using pseudo-announcement dates. Pseudo-announcement dates are computed by subtracting a randomly selected number of trading days from the actual announcement date, where the random numbers are drawn from a uniform distribution spanning 10 to 40 days. Panel A.3 and B.3 compare the differences between actual- and pseudo-announcement dates. Lottery proxies are defined the same as in Table 1. We exclude stocks with a price less than $1 per share at the end of the month prior to the earnings announcements. The sample period is from 1972 to 2014 except for Skewexp which is from 1988 to 2014. Excess returns are reported in percentages. The t-statistics are calculated based on the heteroskedasticity-consistent standard errors of White (1980).

Panel A: (-5,-1) Pre-event Excess Return						
Proxy=	Maxret	Skewexp	Prc	Jackpotp	Ivol	Z-score
Panel A.1: Actual dates						
Q1	0.114	0.219	0.147	0.075	0.096	0.065
Q2	0.207	0.218	0.175	0.173	0.171	0.212
Q3	0.311	0.230	0.192	0.297	0.317	0.266
Q4	0.427	0.420	0.309	0.466	0.418	0.384
Q5	0.452	0.627	0.689	0.646	0.509	0.583
Q5-Q1	0.339	0.408	0.542	0.570	0.413	0.518
t-stat	(3.46)	(3.67)	(5.79)	(5.19)	(3.83)	(4.71)
Panel A.2: Pseudo dates						
Q1	0.057	0.013	0.025	0.012	0.047	0.049
Q2	0.042	0.034	-0.026	0.041	0.053	0.033
Q3	0.072	0.051	0.033	0.056	0.065	0.038
Q4	0.049	0.060	0.014	0.043	0.037	0.036
Q5	-0.008	0.043	0.167	0.082	0.010	0.042
Q5-Q1	-0.064	0.030	0.141	0.071	-0.036	-0.007
t-stat	(-0.91)	(0.31)	(1.71)	(0.80)	(-0.45)	(-0.08)
Panel A.3: Actual dates minus Pseudo dates						
Q1	0.057	0.206	0.122	0.064	0.049	0.016
Q2	0.164	0.185	0.201	0.132	0.118	0.179
Q3	0.239	0.178	0.158	0.241	0.252	0.228
Q4	0.379	0.359	0.295	0.423	0.381	0.348
Q5	0.460	0.584	0.522	0.564	0.499	0.541
Q5-Q1	0.403	0.378	0.401	0.500	0.450	0.525
t-stat	(4.34)	(3.00)	(4.57)	(4.96)	(4.33)	(5.17)

Panel B: (+1,+5) Post-event Excess Return						
Proxy=	Maxret	Skewexp	Prc	Jackpotp	Ivol	Z-score
Panel B.1: Actual dates						
Q1	0.127	0.082	0.097	0.111	0.144	0.167
Q2	0.113	0.058	0.051	0.117	0.106	0.131
Q3	-0.047	-0.019	-0.045	-0.046	-0.013	-0.007
Q4	-0.203	-0.286	-0.274	-0.223	-0.253	-0.303
Q5	-0.633	-0.618	-0.470	-0.535	-0.626	-0.631
Q5-Q1	-0.760	-0.700	-0.567	-0.646	-0.769	-0.798
t-stat	(-7.34)	(-5.68)	(-5.96)	(-5.75)	(-6.87)	(-6.78)
Panel B.2: Pseudo dates						
Q1	0.080	0.011	0.023	0.031	0.055	0.063
Q2	0.052	-0.021	0.025	0.002	0.054	0.041
Q3	0.042	-0.027	0.010	0.046	0.061	0.046
Q4	0.027	-0.043	0.022	0.041	0.025	0.031
Q5	0.004	0.082	0.125	0.106	0.009	0.022
Q5-Q1	-0.076	0.071	0.103	0.075	-0.046	-0.041
t-stat	(-1.1)	(0.82)	(1.44)	(1)	(-0.64)	(-0.54)
Panel B.3: Actual dates minus Pseudo dates						
Q1	0.047	0.070	0.074	0.080	0.088	0.104
Q2	0.062	0.080	0.025	0.115	0.052	0.090
Q3	-0.089	0.007	-0.055	-0.092	-0.074	-0.053
Q4	-0.230	-0.243	-0.296	-0.263	-0.278	-0.334
Q5	-0.637	-0.700	-0.595	-0.641	-0.635	-0.653
Q5-Q1	-0.684	-0.770	-0.669	-0.721	-0.723	-0.757
t-stat	(-6.8)	(-6.67)	(-7.8)	(-6.83)	(-6.82)	(-7.6)

Table 3: Fama-MacBeth Regressions

Each quarter, we run two sets of cross-sectional regressions of (-5,-1) pre-event excess returns (Panel A) and (+1,+5) post-event excess returns (Panel B) on lagged variables for each one of six lottery proxies. If the announcement date is in the first ten trading days of a month, we lag one more month for the control variables. The time-series average of the regression coefficients is reported. Excess returns are defined relative to the value-weighted CRSP index, and in percentages. LogMB is the log of Market-to-Book equity, LogME is the log of market equity, $MOM(-1,0)$ is the return in the last month, $MOM(-12,-1)$ is the cumulative return over the past year with a one-month gap, and $MOM(-36,-12)$ is the cumulative return over the past three years with a one-year gap. Lottery proxies are defined the same as in Table 1. Independent variables (except for returns) are winsorized at their cross-sectional 1st and 99th percentiles. We exclude stocks with a price less than $1 per share at the end of the month prior to the earnings announcements. The sample period is from 1972 to 2014 except for Skewexp which is from 1988 to 2014. The t-statistics are calculated based on the heteroskedasticity-consistent standard errors of White (1980).

Proxy=	Maxret	Skewexp	Prc	Jackpotp	Ivol	Z-score
	Panel A: (-5,-1) Pre-event Regression					
Proxy	1.115	0.327	0.215	6.728	3.534	0.188
	(2.04)	(4.11)	(4.36)	(2.87)	(1.96)	(3.22)
LOGMB	-0.017	0.007	-0.014	-0.022	-0.018	-0.027
	(-0.55)	(0.20)	(-0.43)	(-0.7)	(-0.58)	(-0.93)
LOGME	-0.086	-0.016	-0.029	-0.069	-0.080	-0.040
	(-6.67)	(-0.97)	(-1.94)	(-4.71)	(-6.19)	(-2.34)
MOM(-1,0)	-0.620	-0.402	-0.434	-0.541	-0.560	-0.554
	(-3.17)	(-1.83)	(-2.46)	(-3.08)	(-3.14)	(-3.11)
MOM(-12,-1)	0.447	0.235	0.507	0.441	0.449	0.486
	(6.25)	(2.66)	(7.42)	(6.14)	(6.4)	(7.23)
MOM(-36,-12)	-0.074	-0.033	-0.048	-0.055	-0.073	-0.066
	(-3.07)	(-1.30)	(-2.11)	(-2.54)	(-3.05)	(-2.86)
	Panel B: (+1,+5) Post-event Regression					
Proxy	-4.006	-0.588	-0.371	-14.460	-13.006	-0.396
	(-6.23)	(-7)	(-7.83)	(-4.55)	(-6.07)	(-7.03)
LOGMB	-0.142	-0.181	-0.147	-0.137	-0.136	-0.113
	(-4.52)	(-4.79)	(-4.52)	(-3.99)	(-4.32)	(-3.71)
LOGME	0.060	-0.005	-0.031	0.060	0.049	-0.034
	(4.68)	(-0.26)	(-2.17)	(3.79)	(3.9)	(-2.11)
MOM(-1,0)	-0.406	-0.654	-1.059	-0.865	-0.711	-0.709
	(-2.41)	(-3.51)	(-7.49)	(-5.69)	(-4.77)	(-4.74)
MOM(-12,-1)	-0.196	-0.321	-0.283	-0.227	-0.186	-0.231
	(-3.6)	(-4.72)	(-5.3)	(-3.98)	(-3.48)	(-4.38)
MOM(-36,-12)	-0.001	0.010	-0.052	-0.004	-0.003	-0.021
	(-0.03)	(0.37)	(-2.1)	(-0.17)	(-0.11)	(-0.85)

Table 4: Fama-MacBeth Regressions Controlling for Difference-of-Opinions

Every quarter, we run two cross-sectional regressions of (-5,-1) pre-event excess returns (Panel A.1 and B.1) and (+1,+5) post-event excess returns (Panel A.2 and B.2) on lagged variables. If the announcement date is in the first ten trading days of a month, we lag one more month for the control variables. The time-series average of the regression coefficients is reported. Excess returns are defined relative to the value-weighted CRSP index, and in percentages. LogMB is the log of Market-to-Book equity, LogME is the log of market equity, $MOM(-1,0)$ is the return in the last month, $MOM(-12,-1)$ is the cumulative return over the past year with a one-month gap, and $MOM(-36,-12)$ is the cumulative return over the past three years with a one-year gap. Panel A uses analyst forecast dispersion as the proxy for difference-of-opinions, measured by the standard deviation of all valid forecasts of next quarter's EPS during the period of 90 days prior to the announcement date to 10 days prior to the announcement date, scaled by the absolute value of the mean forecast during the same period. Panel B uses past turnover as the proxy for difference-of-opinions, measured by monthly trading volume divided by number of shares outstanding. To address the issue of double counting of volume for NASDAQ stocks, we follow Anderson and Dyl (2005) and scale down the volume of NASDAQ stocks by 50% before 1997 and 38% after 1997 to make it roughly comparable to the volume on the NYSE. Lottery proxies are defined the same as in Table 1. The intercept of the regression is not reported. Independent variables (except returns) are winsorized at their cross-sectional 1st and 99th percentiles. We exclude stocks with a price less than $1 per share at the end of the month prior to the earnings announcements. The sample period is from 1985 to 2014 except for Skewexp which is from 1988 to 2014 in Panel A, and from 1972 to 2014 except for Skewexp which is from 1988 to 2014 in Panel B. The t-statistics are calculated based on the heteroskedasticity-consistent standard errors of White (1980).

Proxy=	Maxret	Skewexp	Prc	Jackpotp	Ivol	Z-score
Panel A: Fama-MacBeth regressions controlling for forecast dispersion						
Panel A.1: (-5,-1) Pre-event Regression						
Proxy	4.291	0.263	0.276	24.035	12.133	0.372
	(3.77)	(2.17)	(4.36)	(2.79)	(3.23)	(3.83)
LOGMB	0.057	0.071	0.088	0.052	0.053	0.045
	(1.22)	(1.61)	(1.80)	(1.18)	(1.16)	(1.02)
LOGME	-0.015	-0.038	0.026	0.022	-0.005	0.047
	(-0.78)	(-2.01)	(1.31)	(0.88)	(-0.23)	(2.36)
MOM(-1,0)	-0.617	-0.246	-0.108	-0.079	-0.309	-0.336
	(-1.76)	(-0.83)	(-0.35)	(-0.26)	(-0.99)	(-1.08)
MOM(-12,-1)	0.330	0.336	0.392	0.343	0.332	0.387
	(3.18)	(2.72)	(3.76)	(3.21)	(3.24)	(3.69)
MOM(-36,-12)	-0.012	-0.004	0.012	-0.012	-0.015	-0.013
	(-0.38)	(-0.15)	(0.36)	(-0.38)	(-0.48)	(-0.42)
Dispersion	-0.017	-0.001	-0.020	-0.020	-0.023	-0.037
	(-0.42)	(-0.03)	(-0.52)	(-0.55)	(-0.59)	(-0.99)

Proxy=	Maxret	Skewexp	Prc	Jackpotp	Ivol	Z-score
			Panel A.2: (+1,+5) Post-event Regression			
Proxy	-6.723	-0.588	-0.393	-44.185	-22.924	-0.483
	(-5.45)	(-4.73)	(-5.32)	(-5)	(-6.29)	(-5.63)
LOGMB	-0.037	-0.059	-0.070	-0.023	-0.027	-0.017
	(-0.82)	(-1.24)	(-1.49)	(-0.54)	(-0.59)	(-0.37)
LOGME	0.032	-0.010	-0.029	-0.033	0.015	-0.057
	(1.55)	(-0.45)	(-1.28)	(-1.29)	(0.73)	(-2.69)
MOM(-1,0)	-0.064	-0.626	-0.893	-0.697	-0.583	-0.507
	(-0.2)	(-2.18)	(-3.27)	(-2.41)	(-2.05)	(-1.77)
MOM(-12,-1)	-0.347	-0.438	-0.447	-0.394	-0.345	-0.389
	(-3.77)	(-4.39)	(-4.87)	(-4.23)	(-3.84)	(-4.29)
MOM(-36,-12)	0.028	0.030	-0.017	0.018	0.024	0.020
	(0.78)	(0.82)	(-0.49)	(0.53)	(0.69)	(0.58)
Dispersion	-0.049	-0.082	-0.022	-0.058	-0.037	-0.008
	(-1.02)	(-1.61)	(-0.46)	(-1.21)	(-0.77)	(-0.16)
			Panel B: Fama-MacBeth regressions controlling for past turnover			
			Panel B.1: (-5,-1) Pre-event Regression			
Proxy	1.279	0.317	0.199	6.811	4.078	0.180
	(2.48)	(4.50)	(4.32)	(3.09)	(2.34)	(3.53)
LOGMB	-0.019	0.000	-0.015	-0.024	-0.019	-0.028
	(-0.60)	(0.01)	(-0.49)	(-0.79)	(-0.62)	(-0.93)
LOGME	-0.097	-0.042	-0.046	-0.079	-0.091	-0.052
	(-6.80)	(-2.55)	(-3.50)	(-5.06)	(-6.65)	(-3.74)
MOM(-1,0)	-0.567	-0.458	-0.374	-0.470	-0.487	-0.483
	(-2.91)	(-2.12)	(-2.11)	(-2.66)	(-2.71)	(-2.67)
MOM(-12,-1)	0.471	0.245	0.526	0.467	0.474	0.509
	(6.78)	(3.15)	(8.11)	(6.77)	(6.90)	(7.66)
MOM(-36,-12)	-0.075	-0.046	-0.054	-0.056	-0.073	-0.064
	(-3.15)	(-1.78)	(-2.42)	(-2.57)	(-3.09)	(-2.88)
Turnover	-1.007	1.960	-0.801	-0.854	-1.059	-1.238
	(-1.57)	(3.55)	(-1.28)	(-1.32)	(-1.64)	(-2.05)
			Panel B.2: (+1,+5) Post-event Regression			
Proxy	-2.971	-0.603	-0.350	-11.870	-9.717	-0.339
	(-5.01)	(-7.74)	(-7.78)	(-4.05)	(-4.9)	(-6.63)
LOGMB	-0.138	-0.164	-0.135	-0.132	-0.134	-0.112
	(-4.29)	(-4.48)	(-4.14)	(-3.88)	(-4.16)	(-3.58)
LOGME	0.082	0.015	-0.009	0.084	0.073	-0.005
	(5.86)	(0.76)	(-0.67)	(5.19)	(5.54)	(-0.34)
MOM(-1,0)	-0.446	-0.537	-0.957	-0.759	-0.684	-0.666
	(-2.71)	(-2.89)	(-6.61)	(-4.94)	(-4.54)	(-4.37)
MOM(-12,-1)	-0.156	-0.274	-0.238	-0.184	-0.149	-0.194
	(-2.79)	(-4.12)	(-4.4)	(-3.2)	(-2.7)	(-3.55)
MOM(-36,-12)	0.012	0.019	-0.039	0.009	0.010	-0.007
	(0.45)	(0.73)	(-1.56)	(0.33)	(0.41)	(-0.29)
Turnover	-2.377	-2.097	-2.757	-2.679	-2.304	-2.002
	(-4.56)	(-4.16)	(-5.2)	(-4.87)	(-4.32)	(-4.02)

Table 5: Evidence from Retail Trade Imbalance

Each quarter, firms with earnings announcements in that quarter are sorted into five portfolios based on each one of six lottery proxies from the month prior to the announcement date. If the announcement date is in the first ten trading days of a month, we lag one more month for the proxies. Panel A reports the change in retail trade imbalance of bottom and top quintile lottery portfolios and their differences in the pre-event period. We first compute daily retail trade imbalance using the difference between buy-initiated and sell-initiated small-trade volume divided by the total of buy-initiated and sell-initiated small-trade volume: $RIMB = (\text{BUYVOL} - \text{SELLVOL})/(\text{BUYVOL} + \text{SELLVOL})$, where BUYVOL and SELLVOL are the daily buy- and sell- initiated small-trade volume of this stock, respectively. We then take the average of the daily retail trade imbalance during (-10,-6) and (-5,-1) event windows, with day 0 referring to the earnings announcement date. The pre-event change is the (-5,-1) RIMB minus (-10,-6) RIMB, normalized by the absolute value of the (-5,-1) RIMB. Panel B reports the time-series average of the regression coefficients from the Fama-MacBeth predictive regressions. We add two independent variables: (-5,-1) RIMB and its interaction with our lottery proxies into the Fama-MacBeth regressions in Panel B in Table 4. Lottery proxies are defined the same as in Table 1. We only include NYSE and AMEX common stocks, and require the price to be at least \$1 at the end of month prior to the earnings announcements. Independent variables (except returns) are winsorized at their cross-sectional 1st and 99th percentiles. The sample period is from 1983 to 2000 except for Skewexp which is from 1988 to 2000. The t-statistics are calculated based on the heteroskedasticity-adjusted standard errors of Newey-West (1987) in Panel A, and the heteroskedasticity-consistent standard errors of White (1980) in Panel B. We only report the bottom and top quintile lottery portfolios and their differences in Panel A, and the regression coefficients of RIMB, lottery proxies, and the interaction terms in Panel B, to save space.

Proxy=	Maxret	Skewexp	Prc	Jackpotp	Ivol	Z-score
Panel A: (-5,-1) Pre-event change in RIMB of lottery portfolios						
Q1	0.213	-0.030	0.084	0.175	0.177	0.133
Q5	0.242	0.285	0.377	0.285	0.235	0.316
Q5-Q1	0.029	0.314	0.294	0.110	0.059	0.182
t-stat	(1.31)	(6.85)	(2.91)	(2.03)	(2.04)	(4.22)
Panel B: (-5,-1) Pre-event Fama-MacBeth regressions						
RIMB	0.412	0.220	2.598	0.357	0.148	1.166
	(12.97)	(5.30)	(23.86)	(11.08)	(4.21)	(24.63)
Proxy	4.855	1.021	0.531	48.533	20.718	0.581
	(4.89)	(7.19)	(7.6)	(7.72)	(5.57)	(7.00)
Proxy x RIMB	8.840	1.012	0.613	52.743	35.006	0.713
	(14.97)	(16.18)	(19.97)	(16.46)	(17.75)	(17.51)
CONTROLS	YES	YES	YES	YES	YES	YES

Table 6: Fama-MacBeth Regressions with Religious Beliefs Interactions

Each quarter, we run two sets of cross-sectional regressions of (-5,-1) pre-event excess returns (Panel A) and (+1,+5) post-event excess returns (Panel B) on lagged variables. If the announcement date is in the first ten trading days of a month, we lag one more month for the control variables. The time-series average of the regression coefficients is reported. Excess returns are defined relative to the value-weighted CRSP index, and in percentages. LogCPRATIO is the log of Catholic-Protestant ratio from Kumar et al. (2011). LogMB is the log of Market-to-Book equity, LogME is the log of market equity, $MOM(-1,0)$ is the return in the last month, $MOM(-12,-1)$ is the cumulative return over the past year with a one-month gap, and $MOM(-36,-12)$ is the cumulative return over the past three years with a one-year gap. Lottery proxies are defined the same as in Table 1. Independent variables (except returns) are winsorized at their cross-sectional 1st and 99th percentiles. We exclude stocks with a price less than $1 per share at the end of the month prior to the earnings announcements. The sample period is from 1972 to 2010 except for Skewexp which is from 1988 to 2010. The t-statistics are calculated based on the heteroskedasticity-consistent standard errors of White (1980).

Proxy=	Maxret	Skewexp	Prc	Jackpotp	Ivol	Z-score
Panel A: (-5,-1) Pre-event Regression						
LOGCPRATIO	-0.001	0.010	0.104	0.002	-0.020	0.034
	(-0.07)	(0.50)	(2.06)	(0.11)	(-0.84)	(2.69)
Proxy	1.967	0.400	0.245	8.329	6.434	0.247
	(3.49)	(5.00)	(4.79)	(3.56)	(3.54)	(4.74)
Proxy x LOGCPRATIO	0.722	0.052	0.026	1.785	2.709	0.032
	(2.16)	(1.95)	(1.61)	(1.32)	(2.41)	(2.08)
LOGMB	-0.020	0.000	-0.014	-0.024	-0.023	-0.032
	(-0.59)	(0.01)	(-0.4)	(-0.70)	(-0.66)	(-0.95)
LOGME	-0.101	-0.040	-0.039	-0.081	-0.091	-0.037
	(-6.43)	(-2.09)	(-2.4)	(-4.72)	(-6.01)	(-2.43)
MOM(-1,0)	0.058	-0.328	0.337	0.213	0.180	0.176
	(0.24)	(-1.27)	(1.54)	(0.97)	(0.8)	(0.79)
MOM(-12,-1)	0.521	0.290	0.577	0.509	0.527	0.556
	(6.21)	(3.12)	(7.37)	(6.31)	(6.3)	(6.87)
MOM(-36,-12)	-0.075	-0.059	-0.048	-0.058	-0.068	-0.059
	(-3.06)	(-1.98)	(-2.02)	(-2.57)	(-2.84)	(-2.55)
Turnover	-1.838	2.078	-1.246	-1.324	-1.847	-1.996
	(-2.32)	(3.35)	(-1.64)	(-1.65)	(-2.26)	(-2.59)
Panel B: (+1,+5) Post-event Regression						
LOGCPRATIO	-0.041	0.011	-0.081	-0.012	-0.027	-0.014
	(-2.34)	(0.41)	(-1.82)	(-0.73)	(-1.3)	(-1.21)
Proxy	-2.703	-0.614	-0.331	-9.677	-9.090	-0.313
	(-3.94)	(-6.81)	(-6.76)	(-3.1)	(-4.16)	(-5.8)
Proxy x LOGCPRATIO	0.271	-0.051	-0.024	-0.755	0.118	-0.014
	(0.91)	(-1.45)	(-1.69)	(-0.68)	(0.13)	(-0.98)
LOGMB	-0.141	-0.162	-0.140	-0.154	-0.136	-0.113
	(-3.87)	(-3.87)	(-3.79)	(-3.99)	(-3.72)	(-3.21)
LOGME	0.089	0.006	-0.002	0.090	0.081	0.003
	(5.74)	(0.27)	(-0.16)	(4.93)	(5.48)	(0.2)
MOM(-1,0)	-0.618	-0.720	-1.084	-0.928	-0.838	-0.801
	(-3.32)	(-3.41)	(-6.5)	(-5.55)	(-4.98)	(-4.65)
MOM(-12,-1)	-0.180	-0.349	-0.261	-0.194	-0.174	-0.217
	(-2.96)	(-4.75)	(-4.38)	(-3.05)	(-2.89)	(-3.59)
MOM(-36,-12)	0.006	0.003	-0.047	-0.004	0.002	-0.016
	(0.19)	(0.09)	(-1.67)	(-0.14)	(0.07)	(-0.61)
Turnover	-3.135	-2.296	-3.554	-3.503	-2.989	-2.703
	(-4.4)	(-3.88)	(-5.2)	(-4.82)	(-4.17)	(-3.96)

Table 7: Pre-event and Post-event Portfolio Returns among Bottom and Top 50% IO Subsample

Each quarter, firms with earnings announcements are first divided into 2 groups based on the institutional ownership (IO). Within each IO group, firms are further sorted into five portfolios based on each one of six lottery proxies from the month prior to the announcement date. If the announcement date is in the first ten trading days of a month, we lag one more month for the proxies. We report equal-weighted excess returns of these lottery portfolios, and the differences between top and bottom quintile portfolios during the (-5,-1) pre-event period in Panel A.1 and the (+1,+5) post-event period in Panel B.1, with day 0 referring to the earnings announcement date. IO is calculated as the percentage of firms' shares held by institutional investors at the end of prior quarter. Lottery proxies are defined the same as in Table 1. We exclude stocks with a price less than $1 per share at the end of the month prior to the earnings announcements. The sample period is from 1980 to 2014 except for Skewexp which is from 1988 to 2014. Excess returns are reported in percentages. The t-statistics are calculated based on the heteroskedasticity-consistent standard errors of White (1980). We only report the bottom and top quintile lottery portfolios and their differences to save space.

Proxy=	Maxret	Skewexp	Prc	Jackpotp	Ivol	Z-score
Panel A: (-5,-1) Pre-event Excess Return						
Panel A.1: Bottom 50% IO subsample						
Q1	0.117	0.176	0.141	0.169	0.145	0.118
Q5	0.520	0.727	0.752	0.727	0.575	0.624
Q5-Q1	0.403	0.551	0.611	0.558	0.430	0.506
t-stat	(3.45)	(4.07)	(4.62)	(4.23)	(3.28)	(3.72)
Panel A.2: Top 50% IO subsample						
Q1	0.025	0.257	0.158	0.068	0.050	0.042
Q5	0.337	0.301	0.227	0.291	0.342	0.316
Q5-Q1	0.312	0.044	0.069	0.223	0.291	0.274
t-stat	(2.66)	(0.35)	(0.67)	(1.74)	(2.24)	(1.98)
Panel A.3: Top minus Bottom 50% IO subsample						
Q5-Q1	-0.091	-0.508	-0.542	-0.335	-0.138	-0.232
t-stat	(-1.04)	(-4.07)	(-4.93)	(-3.13)	(-1.45)	(-2.22)
Panel B: (+1,+5) Post-event Excess Return						
Panel B.1: Bottom 50% IO subsample						
Q1	0.070	-0.111	-0.103	-0.043	0.061	0.093
Q5	-0.896	-0.822	-0.687	-0.760	-0.846	-0.824
Q5-Q1	-0.967	-0.711	-0.584	-0.717	-0.908	-0.917
t-stat	(-6.87)	(-5.07)	(-4.69)	(-4.88)	(-6.05)	(-6.03)
Panel B.2: Top 50% IO subsample						
Q1	0.146	0.108	0.123	0.135	0.176	0.204
Q5	-0.214	-0.066	-0.079	-0.037	-0.220	-0.208
Q5-Q1	-0.359	-0.174	-0.202	-0.172	-0.395	-0.412
t-stat	(-3.13)	(-1.31)	(-1.75)	(-1.31)	(-3.01)	(-2.94)
Panel B.3: Top minus Bottom 50% IO subsample						
Q5-Q1	0.607	0.537	0.382	0.545	0.512	0.505
t-stat	(5.91)	(4.36)	(3.31)	(4.34)	(4.72)	(4.63)

Table 8: Pre-event and Post-event Portfolio Returns for Non-US G7 Countries

This table reports the pre-event and post-event portfolio returns for non-US G7 countries. Each quarter in each country, firms with earnings announcements are divided into five portfolios based on a composite z-score of three lottery proxies (Maxret, Prc, and Ivol) from the month prior to the announcement date. If the announcement date is in the first ten trading days of a month, we lag one more month for the proxies. Maxret is the maximum daily return, Prc is negative log of one plus stock price, i.e., $Prc = -log(1 + \text{Price})$, and Ivol is idiosyncratic volatility from Ang, Hodrick, Xing, and Zhang (2009). We report equal-weighted excess returns of these z-score portfolios, and the differences between top and bottom quintile portfolios during the (-5,-1) pre-event period in Panel A and the (+1,+5) post-event period in Panel B, with day 0 referring to the earnings announcement date. Detailed variable definitions are described in the Appendix. The sample period is from September 1999 to December 2014 for Canada, April 2002 to December 2014 for Germany, January 2004 to September 2014 for France, January 1994 to December 2014 for UK, April 2003 to December 2014 for Italy, and October 2001 to December 2014 for Japan. Excess returns are reported in percentages. The t-statistics are calculated based on the heteroskedasticity-consistent standard errors of White (1980).

Country	Canada	Germany	France	UK	Italy	Japan
Panel A: (-5,-1) Pre-event Excess Return						
Q1	-0.043	0.080	0.317	0.462	0.424	0.232
Q2	-0.042	0.379	0.088	0.581	0.063	0.035
Q3	0.336	0.505	0.243	0.573	-0.019	0.057
Q4	0.175	0.603	0.466	0.769	0.172	0.133
Q5	0.601	1.281	0.964	0.818	-0.042	0.253
Q5-Q1	0.644	1.202	0.647	0.355	-0.466	0.020
t-stat	(2.14)	(3.58)	(2.4)	(1.85)	(-2.07)	(0.12)
Panel B: (+1,+5) Post-event Excess Return						
Q1	0.185	0.012	-0.074	0.693	-0.159	-0.066
Q2	-0.311	-0.328	0.224	0.697	-0.442	-0.230
Q3	-0.347	-0.278	0.332	0.737	-0.439	-0.504
Q4	-0.608	-0.877	0.158	0.517	-0.710	-0.530
Q5	-0.491	-1.110	-0.648	-0.310	-0.999	-1.395
Q5-Q1	-0.676	-1.122	-0.574	-1.003	-0.839	-1.330
t-stat	(-2.84)	(-3.38)	(-1.85)	(-5.51)	(-3.03)	(-5.98)

Table 9: Realized Skewness of Event Returns and Earnings Surprises

Each quarter, firms with earnings announcements in that quarter are sorted into five portfolios based on each one of six lottery proxies from the month prior to the announcement date. If the announcement date is in the first ten trading days of a month, we lag one more month for the proxies. We report the skewness (Panel A.1) of firm-quarter panel excess returns during the (-1,+1) 3-day event-window centered at the announcement date for the top and bottom quintile portfolios, and their differences. We also present analogous skewness (Panel A.2) using pseudo-announcement dates. Pseudo-announcement dates are computed by subtracting a randomly selected number of trading days from the actual announcement date, where the random numbers are drawn from a uniform distribution spanning 10 to 40 days. Panel A.3 compares the differences between actual- and pseudo-announcement dates. Panel B reports the skewness of firm-quarter panel earnings surprise at the announcement date for the top and bottom quintile portfolios, and their differences. The earnings surprise is calculated by taking the difference between actual quarterly earnings per share and the most recent median consensus EPS forecast of analysts for that quarter normalized by assets per share at previous quarter end. Lottery proxies are defined the same as in Table 1. We exclude stocks with a price less than $1 per share at the end of the month prior to the earnings announcements. The sample period is from 1972 to 2014 in Panel A, from 1985 to 2014 in Panel B, and from 1988 to 2014 for Skewexp in both panels. We only report the bottom and top quintile lottery portfolios and their differences to save space.

Proxy=	Maxret	Skewexp	Prc	Jackpotp	Ivol	Z-score
Panel A: skewness of (-1,+1) Excess Return						
Panel A.1: Actual dates						
Q1	1.468	0.278	0.079	0.203	0.645	0.118
Q5	3.601	4.156	4.011	3.981	3.732	3.890
Q5-Q1	2.134	3.878	3.932	3.778	3.087	3.772
Panel A.2: Pseudo dates						
Q1	1.263	0.177	-0.445	0.832	0.747	0.681
Q5	1.583	-0.680	2.267	1.694	1.492	0.973
Q5-Q1	0.320	-0.857	2.712	0.862	0.745	0.292
Panel A.3: Actual dates minus Pseudo dates						
Q1	0.205	0.101	0.524	-0.628	-0.102	-0.563
Q5	2.018	4.836	1.744	2.287	2.240	2.917
Q5-Q1	1.813	4.735	1.220	2.916	2.343	3.480
Panel B: Skewness of earnings surprise						
Q1	-3.900	-2.651	-1.419	-4.363	-4.234	-3.874
Q5	-1.342	-1.146	-1.107	-1.159	-1.213	-1.083
Q5-Q1	2.559	1.506	0.312	3.204	3.021	2.791

Table 10: Alternative Definition of Earnings Announcement Dates

Each quarter, firms with earnings announcements in that quarter are sorted into five portfolios based on each one of six lottery proxies from the month prior to the announcement date. If the announcement date is in the first ten trading days of a month, we lag one more month for the proxies. We report equal-weighted excess returns of these lottery portfolios, and the differences between top and bottom quintile portfolios during the (-5,-1) pre-event period in Panel A and the (0,+5) post-event period in Panel B, with day 0 referring to the earnings announcement date. The earnings announcement date is defined following Engelberg, McLean, and Pontiff (2018): for each firm, we first compute its daily trading volume scaled by market trading volume for each day before, the day of, and the day after the reported earnings announcement date from Compustat quarterly database. The highest relative trading volume day among these three days is treated as the earnings announcement day. Lottery proxies are defined the same as in Table 1. We exclude stocks with a price less than $1 per share at the end of the month prior to the earnings announcements. The sample period is from 1972 to 2014 except for Skewexp which is from 1988 to 2014. Excess returns are reported in percentages. The t-statistics are calculated based on the heteroskedasticity-consistent standard errors of White (1980).

Proxy=	Maxret	Skewexp	Prc	Jackpotp	Ivol	Z-score
	Panel A: (-5,-1) Pre-event Excess Return					
Q1	0.090	0.184	0.109	0.038	0.074	0.037
Q2	0.159	0.146	0.132	0.139	0.121	0.168
Q3	0.268	0.189	0.171	0.234	0.260	0.216
Q4	0.370	0.346	0.258	0.416	0.386	0.343
Q5	0.417	0.589	0.634	0.616	0.461	0.538
Q5-Q1	0.327	0.405	0.526	0.578	0.387	0.501
t-stat	(3.42)	(3.64)	(5.65)	(5.4)	(3.68)	(4.59)
	Panel B: (0,+5) Post-event Excess Return					
Q1	0.293	0.203	0.231	0.225	0.303	0.300
Q2	0.334	0.226	0.219	0.308	0.328	0.325
Q3	0.132	0.172	0.098	0.182	0.182	0.189
Q4	-0.016	-0.091	-0.132	-0.018	-0.103	-0.142
Q5	-0.493	-0.290	-0.165	-0.287	-0.460	-0.423
Q5-Q1	-0.786	-0.493	-0.396	-0.512	-0.763	-0.723
t-stat	(-6.87)	(-3.5)	(-3.55)	(-3.91)	(-6.1)	(-5.55)

Table 11: Pre-event Portfolio Returns among Early/On-time/Late Announcers

Each quarter, firms with earnings announcements in that quarter are sorted into five portfolios based on each one of six lottery proxies from the month prior to the announcement date. If the announcement date is in the first ten trading days of a month, we lag one more month for the proxies. We report equal-weighted excess returns of these lottery portfolios and the differences between top and bottom quintile portfolios during the (-5,-1) pre-event periodwithin the subsample of early (Panel A), on-time (Panel B), and late (Panel C) announcers relative to the expected earnings announcement dates. Expected earnings announcement dates are calculated by adding the historical reporting lag to the current fiscal quarter end. The historical reporting lag is the median number of trading days between a firm's fiscal quarter end and its actual announcement dates for the same fiscal quarter over the previous ten years. Early, on-time, and late announcers are firms whose actual announcement dates are more than one day before, within one day, and more than one day after the expected earnings announcement dates, respectively. Lottery proxies are defined the same as in Table 1. We exclude stocks with a price less than $1 per share at the end of the month prior to the earnings announcements. The sample period is from 1972 to 2014 except for Skewexp which is from 1988 to 2014. Excess returns are reported in percentages. The t-statistics are calculated based on the heteroskedasticity-consistent standard errors of White (1980).

Proxy=	Maxret	Skewexp	Prc	Jackpotp	Ivol	Z-score
Panel A: Early announcers						
Q1	0.183	0.309	0.263	0.185	0.164	0.129
Q5	1.043	1.182	1.347	1.405	1.089	1.324
Q5-Q1	0.860	0.873	1.084	1.220	0.926	1.195
t-stat	(7.18)	(6.31)	(10.36)	(8.65)	(6.90)	(8.95)
Panel B: On-time announcers						
Q1	0.152	0.189	0.204	0.098	0.112	0.085
Q5	0.452	0.610	0.715	0.606	0.509	0.573
Q5-Q1	0.299	0.421	0.510	0.508	0.398	0.488
t-stat	(2.36)	(3.12)	(4.09)	(3.73)	(2.86)	(3.53)
Panel C: Late announcers						
Q1	0.008	0.148	0.073	0.027	0.018	0.004
Q5	-0.006	0.242	0.138	0.093	0.063	0.031
Q5-Q1	-0.013	0.093	0.065	0.066	0.045	0.028
t-stat	(-0.12)	(0.70)	(0.51)	(0.52)	(0.37)	(0.20)

Table 12: Aggregate mutual fund flows, hedge fund flows, and lottery spread

This table reports the coefficients of two quarterly time series regressions of return spreads between top and bottom lottery quintile portfolios on contemporaneous aggregate mutual fund flow (MFFLOW) and aggregate hedge fund flow (HFFLOW). (Panel A) is based on the (-5,-1) pre-event window, and Panel B is based on the (+1,+5) post-event window. Following Akbas, Armstrong, Sorescu, and Subrahmanyam (2015), monthly aggregate MFFLOW is defined as: $MFFLOW_t = \frac{\sum_{i=1}^{N}[TNA_{i,t} - TNA_{i,t-1}(1+MRET_{i,t})]}{\sum_{i=1}^{N} TNA_{i,t-1}}$, where $TNA_{i,t}$ is the total net assets of mutual fund i in month t, $MRET_{i,t}$ is the monthly return of mutual fund i in month t, net of fees. Monthly aggregate HFFLOW is defined as: $HFFLOW_t = \frac{\sum_{i=1}^{N}[TNA_{i,t} - TNA_{i,t-1}(1+HRET_{i,t})]}{\sum_{i=1}^{N} TNA_{i,t-1}}$, where $TNA_{i,t}$ is the total net assets of hedge fund i in month t, $HRET_{i,t}$ is the monthly return of hedge fund i in month t, net of fees. The quarterly MFFLOW and HFFLOW are the sum of monthly MFFLOW and HFFLOW within a quarter, respectively. Lottery proxies are defined the same as in Table 1. The intercept is include but not reported to save space. The sample period is from 1994Q1 to 2014Q4. The t-statistics are calculated based on the heteroskedasticity-consistent standard errors of White (1980).

Proxy=	Maxret	Skewexp	Prc	Jackpotp	Ivol	Z-score
	Panel A: (-5,-1) Pre-event Regression					
MFFLOW	0.336	0.144	0.224	0.302	0.287	0.271
	(2.76)	(1.49)	(1.95)	(2.44)	(2.21)	(2.1)
HFFLOW	-0.044	0.000	-0.043	-0.037	-0.037	-0.038
	(-0.93)	(-0.01)	(-0.99)	(-0.6)	(-0.78)	(-0.75)
	Panel B: (+1,+5) Post-event Regression					
MFFLOW	0.499	0.474	0.565	0.612	0.631	0.667
	(5.28)	(5.16)	(6.21)	(5.56)	(6.19)	(5.89)
HFFLOW	-0.139	-0.100	-0.105	-0.119	-0.165	-0.149
	(-2.38)	(-2.86)	(-1.93)	(-2.03)	(-2.59)	(-2.34)

Table 13: Enhanced Lottery Strategy

This table compares the monthly return spreads of the standard lottery strategy (Panel A), our refined lottery strategy (Panel B), and their differences (Panel C). The standard lottery strategy is constructed by holding a hedge portfolio from longing bottom quintile lottery portfolios and shorting top quintile lottery portfolios. Each month, stocks are divided into 5 portfolios based on each one of six lottery proxies from the previous month. Our refined lottery strategy adds a pre-event strategy to the standard lottery strategy. Firms with earnings announcements in a certain month are bought if they belong to the top quintile lottery portfolios and sold if they belong to bottom quintile lottery portfolios during the (-10,-1) pre-event window. To ensure that the strategy is implementable, we only use the pre-event days after the portfolio formation date. The portfolio is held for one month and value-weighted excess return and Fama-French four-factor alpha spreads are calculated. Lottery proxies are defined the same as in Table 1. We exclude stocks with price less than $1 at the end of the previous month. The sample period is from 1972 to 2014 except for Skewexp which is from 1988 to 2014. Excess returns and FF4 alphas are reported in percentages. The t-statistics are calculated based on the heteroskedasticity-consistent standard errors of White (1980). We only report the bottom and top quintile lottery portfolios and their differences to save space.

Proxy=	Maxret	Skewexp	Prc	Jackpotp	Ivol	Z-score
Panel A: Standard lottery strategy						
Q1	0.577	0.790	0.522	0.547	0.568	0.583
Q5	0.145	0.211	0.523	-0.186	-0.244	-0.449
R^e_{Q1-Q5}	0.432	0.579	-0.001	0.733	0.811	1.031
t-stat	(1.59)	(1.61)	(0.00)	(2.10)	(2.76)	(2.99)
α^{FF4}_{Q1-Q5}	0.514	0.412	-0.006	0.835	0.881	1.085
t-stat	(2.95)	(1.82)	(-0.03)	(4.36)	(4.85)	(5.01)
Panel B: Refined lottery strategy						
Q1	0.359	0.460	0.256	0.271	0.299	0.322
Q5	-0.236	-0.277	-0.165	-0.729	-0.586	-0.910
R^e_{Q1-Q5}	0.595	0.737	0.421	1.000	0.885	1.231
t-stat	(2.58)	(2.54)	(1.5)	(3.45)	(3.55)	(4.22)
α^{FF4}_{Q1-Q5}	0.810	0.795	0.597	1.288	1.144	1.500
t-stat	(4.16)	(3.37)	(2.53)	(6.55)	(6.31)	(7.30)
Panel C: Refined strategy minus standard strategy						
Q1	-0.218	-0.329	-0.266	-0.276	-0.269	-0.261
Q5	-0.381	-0.488	-0.689	-0.543	-0.342	-0.461
R^e_{Q1-Q5}	0.163	0.158	0.422	0.267	0.073	0.200
t-stat	(1.23)	(0.94)	(3.20)	(1.71)	(0.55)	(1.46)
α^{FF4}_{Q1-Q5}	0.295	0.382	0.603	0.453	0.263	0.415
t-stat	(1.79)	(2.10)	(3.71)	(2.45)	(1.61)	(2.48)

Appendix: Definitions of Key Variables

This appendix provides the details for constructing the lottery measures.

Skewexp: The expected idiosyncratic skewness is calculated in two steps following Boyer, Mitton, and Vorkink (2010) (Table 2, Model 6, page 179). First, we estimate the following cross-sectional regressions separately at the end of each month t:

$$is_{i,t} = \beta_{0,t} + \beta_{1,t} is_{i,t-60} + \beta_{2,t} iv_{i,t-60} + \lambda_t^{'} X_{i,t-60} + \varepsilon_{i,t},$$

where $is_{i,t}$ and $iv_{i,t}$ denote the historical estimates of idiosyncratic volatility and skewness relative to the Fama and French three-factor model, respectively, for firm i using daily stock data over the past 60 months till month t. $X_{i,t}$ is a set of firm-specific variables including momentum as the cumulative returns over months $t-72$ through $t-61$, turnover as the average daily turnover in month $t-60$, the small-size market capitalization dummy, the medium-size market capitalization dummy, the industry dummy based on the Fama-French 17-industries definition, and the NASDAQ dummy. After we have these regression parameters, the expected idiosyncratic skewness for each firm i at the end of each month t is then computed in the second step:

$$Skewexp_t \equiv E_t[is_{i,t+60}] = \beta_{0,t} + \beta_{1,t} is_{i,t} + \beta_{2,t} iv_{i,t} + \lambda_t^{'} X_{i,t}.$$

Similar to Boyer, Mitton, and Vorkink's (2010) baseline database, our expected idiosyncratic skewness measure dates back to January 1988.

Jackpotp: The predicted jackpot probability is constructed from the baseline model in Conrad, Kapadia, and Xing (2014) (Table 3, Panel A, page 461). In particular, for each firm, we first estimate the baseline logit model using data from the past 20 years at the end of June every year:

$$Prob_{t-1}(Jackpot_{i,t} = 1) = \frac{exp(a + b \times X_{i,t-1})}{1 + exp(a + b \times X_{i,t-1})},$$

where $Jackpot_{i,t}$ is a dummy that equals 1 if firm i's log return in the next 12 month period is larger than 100%. The vector $X_{i,t-1}$ is a set of firm-specific variables known at time $t-1$, including skewness of log daily returns (centered around 0) over the last 3 months, log stock return over the past year, firm age as the number of years since appearance on CRSP, asset tangibility as the ratio of gross PPE (property plant and equipment) to total assets, the log of sales growth over the prior year, detrended stock turnover as the difference between the average past 6-month turnover and the average past 18-month turnover, volatility as the standard deviation of daily returns (centered around 0) over the past 3 months, and the log of market equity in thousands. Next, we use these estimated parameters to construct the out-of-sample predicted jackpot probability (Jackpotp). We reestimate this model for each firm every year from 1951, so our first set of out-of-sample predicted jackpot probabilities is from January 1972.

Ivol: The idiosyncratic stock return volatility is constructed following Ang, Hodrick, Xing, and Zhang (2006). In particular, we measure IVOL by the standard deviation of the residual values from the following time-series model:

$$R_{i,t} = b_0 + b_1 R_{M,t} + b_2 SMB_t + b_3 HML_t + \varepsilon_{i,t}, \tag{1}$$

where $R_{i,t}$ is stock i's daily excess return on date t, and $R_{M,t}$, SMB_t, and HML_t are the market factor, size factor, and value factor on date t, respectively.[24] We estimate the above equation for each stock each month in the data set using the daily return from the previous month with a minimum requirement of 10 nonmissing values.[25]

Z-score: Z-score is a monthly composite lottery measure calculated as the average of the individual z-scores of the following five lottery measures: Maxret, Skewexp, Prc, Jackpotp, and Ivol. Each month for each stock, each one of the five lottery measures is first converted into its rank and then standardized to obtain its z-score: $z = (r - \mu_r)/\sigma_r$, where r is the rank of this measure, μ_r and σ_r are the cross sectional mean and standard deviation of r. The composite z-score is the average of these five z-scores. We require a minimum of three nonmissing z-scores to compute this measure.

Non-US G7 countries: Following Gao et al (2015), for each country, we only include common stocks traded on its major national stock exchanges. Most countries have only one major exchange except for Canada, for which we use stocks from both the Toronto Stock Exchange and the TSX Ventures Exchange, and Japan, for which we include all stocks traded on the Osaka Securities Exchange, the Tokyo Stock Exchange, and JASDAQ. We convert all returns, prices, and accounting variables from local currency to US dollars. We further exclude micro-cap firms which have market equity below 5% in each quarter in a country. Returns are winsorized at 0.5 and 99.5 percentiles to avoid extreme values.

[24] We thank Ken French for providing updated series for these factors.

[25] Our results are not sensitive to this cutoff.

To measure the lottery feature of international stocks, we use three proxies similar to our definitions for US stocks: Maxret is the maximum daily return within a month, and Prc is negative log of one plus month-end stock price, i.e., $Prc = -log(1 + \text{Price})$). To compute Ivol for each country, we first specify a local version of the Fama-French three-factor model including a local market excess return factor, a local size factor, and a local value factor, following Ang et al. (2009) and Gao et al. (2015). The market factor is the value-weighted return of the local market portfolio minus the one-month U.S. T-bill rate. The country-specific size is the return spread between the smallest and biggest local firms, and the value factor is the spread between the local value and growth firms. The idiosyncratic volatility (Ivol) is computed as the standard idiosyncratic volatility measure, i.e., the standard deviation of residuals from the daily local factor model within a month with a minimum requirement of 10 nonmissing values. After we obtain Maxret, Prc, and Ivol for each stock, we construct a composite z-score as the average of these individual z-scores.

Further, to ensure the accuracy of earnings announcement dates for international countries, we only use dates that can be confirmed from multiple available data sources. In particular, we require the dates to exist in both Thomson Reuters Worldscope database and Bloomberg for non-US G7 countries except for Canada, for which we require the dates to exist in all three data sources: Thomson Reuters Worldscope database, Compustat North American database and Bloomberg. Lastly, we require a minimum of 50 stocks when forming portfolios to avoid the potential bias from having portfolios with too few assets.