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Doran, James and Jiang, Danling and Peterson, David

Florida State University, Florida State University, Florida State University

8 April 2008

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James S. Doran†

Danling Jiang‡

David R. Peterson§

March 10, 2009

*We appreciate helpful comments and suggestions on earlier drafts from Hal Arkes, Don Autore, Gurdip Bakshi, Robert Battalio, Gary Benesh, Jie Cao, Honghui Chen, Mike Cliff, Gonul Colak, John Griffin, David Hirshleifer, Irena Hutton, Narasimhan Jegadeesh, Alok Kumar, Xiaoding Liu, Chris James, Sonya Lim, Roger Loh, Mahendrarajah Nimalendran (Nimal), Jay Ritter, Hersh Shefrin, K.R. Subramanyam, Rossen Valkanov, Yexiao Xu and seminar participants at Florida State University and University of Florida, conference participants at the 2008 BDRM conference hosted by Rady School of Management in UCSD, 2008 China International conference in finance in Dalian, China, and 2008 FMA at Dallas, Texas. We appreciate Ji-Woong Chung and Kuan-Hui Lee for kindly answering questions about Datastream, and Ansley Chua and Dan Lawson for helpful research assistance. This paper subsumes the earlier version entitled "Gambling in the New Year? The January Idiosyncratic Volatility Puzzle." All errors remain ours.

†Bank of America Professor of Finance, College of Business, The Florida State University. (850)644-7868, jsdoran@cob.fsu.edu, http://www.jamesdoran.org/.

‡Corresponding author. Assistant professor, College of Business, The Florida State University. (850)645-1519, djiang@cob.fsu.edu, http://mailer.fsu.edu/∼djiang/.

§Wachovia Professor of Finance, College of Business, The Florida State University. (850)644-8200, dpeterson@cob.fsu.edu, http://www.cob.fsu.edu/fin/vita/dpeterson.pdf.

Gambling Preference and the New Year Effect of Assets with Lottery Features

Abstract

This paper examines whether investors exhibit a New Year's gambling preference and whether such preference impacts prices and returns of assets with lottery features. In January, calls options have higher demand than put options, especially by small investors. In addition, relative to at-the-money calls, out-of-the-money calls are the most expensive and actively traded. In the equity markets, lottery-type stocks in the US outperform their counterparts mainly in January, but tend to underperform in other months. Lottery-type Chinese stocks outperform in the Chinese New Year month, but not in January. This New Year effect provides new insights into the broad phenomena related to the January effect.

[Keywords] January effect, Gambling, Preference for skewness, Out-of-the-money options, China

[JEL Classification] G12, G14

"In addition to celebrating the new year last night, lottery players from around the United States were checking their raffle tickets to see if they would start 2008 as a new millionaire."

— "New Year's Eve lottery raffles from around the USA"
Lotterypost.com, January 1, 2008

"Chinese people at New Year's time always gamble...If you gamble and win, then it is good luck at the beginning of the year; through all year round you will make money."

—"Las Vegas bets big on Lunar New Year"
San Francisco Chronicle, February 10, 2008

1. Introduction

Individuals' preference to gamble has long been noted by financial economists as an explanation for a number of aspects of individual financial decision making, such as the purchase of both insurance and lotteries (Friedman and Savage 1948; Markowitz 1952), portfolio underdiversification (Statman 2004), and portfolio overweighting on lottery-like securities (Kumar 2009). Recent theoretical development (Shefrin and Statman 2000; Barberis and Huang 2008; Brunnermeier, Gollier, and Parker 2007; Mitton and Vorkink 2007) advances this notion into asset pricing. These theories show that a gambling preference by part of the market participants can cause overpricing of securities with lottery features.

Evidence from gambling and individual risk taking further suggests that individuals may exhibit stronger gambling mentality in the New Year. There is anecdotal evidence showing that individuals from the US and around the world actively engage in lottery plays, casino gambling, and home gaming to celebrate the New Year. Experimental work on individual decision making finds that people tend to engage in risk seeking activities after experiencing outcome payoffs in prior rounds of gambling (Thaler and Johnson 1990), and that multi-period financial decisions are commonly evaluated in intertemporal mental accounts (Thaler 1985), which can be labeled by year. As a natural starting point for a new round of gambling/investing, risk taking is likely to strengthen in the New Year. Furthermore, since at the turn of the New Year investors usually receive annual reports from mutual funds, prepare taxes, or receive bonuses, they most likely evaluate portfolios, make New Year's resolutions, and throw some money for a chance of a "home run" in the stock market.[1]

[1]Benartzi and Thaler (1995) suggest that receiving annual reports and filing taxes at the year-end likely force investors to evaluate and reallocate their portfolios. Employees on Wall Street typically get their bonus numbers in the first two weeks of December – with the cash coming early in the New Year. See "Goldman Chiefs Give Up Bonuses," by Susanne Craig, Wall Street Journal, 11/17/2008.

In this paper, we examine whether investors exhibit the New Year's gambling mentality in the financial markets and whether such gambling preference impacts prices, returns, and trading volume of assets with lottery features. We hypothesize that investors most likely place lottery-type bets in financial markets at the start of a new year, elevating prices and returns of lottery-like options and stocks at that time. Furthermore, in markets such as China where investors celebrate the Chinese New Year that is different from January 1**st**, lottery-like stocks should outperform at the start of the Chinese New Year, but not necessarily in January. We find strong evidence supporting the above hypotheses. The pricing impacts are economically and statistically significant. Our evidence offers new insights into several well-known January effects.

We begin our tests with the US option markets. Behavioral theories (Shefrin and Statman 2000; Barberis and Huang 2008) suggest that out-of-the-money (OTM) call options are natural candidates for gambling purposes. Like lotteries, OTM calls are cheap and have highly skewed payoffs. If at the turn of the year investors desire to purchase lottery-type assets, they will over-demand OTM calls and drive up the prices and volume of these securities. Using at-the-money (ATM) calls on the same stocks as benchmarks, we show that, indeed, the implied volatility (which measures the relative expensiveness of options) and the volume on the OTM calls are significantly greater in January than in other months. This evidence reveals novel seasonality in option markets that are consistent with the New Year's gambling mentality of investors.

We also examine trading behaviors from accounts of clearing member firms (which mostly include big institutions) versus customers (including, among others, retail investors) across exchanges. We expect that, relative to firms, customers more likely place open buy orders on call than on put options, particularly in January.[2] This is consistent with the notion that unsophisticated investors usually bet on calls rather than on puts for upside potentials (Shefrin and Statman 2000; Statman 2002). Indeed, we find that customers, particularly those who place small bets per trade, significantly open more buy contracts on calls than puts, and particularly in January. Relative to firms, customers also favor cheaper options, measured by the option premium, again especially in January. Interestingly, such differentials in preference between January and non-January months are absent for open put buys. In other words, our evidence suggests that in the option markets small investors exhibit strong gambling preferences in the New Year, and reveal such preferences

[2] Open buys refer to new purchases of options and do not include buying to cover previous short option positions.

through buying OTM calls.

Does the New Year's gambling mentality in the option markets translate to equity markets and impact stock prices and returns? We explore this question in the equity markets of the US and China. In the US stock markets, we employ three measures of stock lottery features following Kumar (2009): low stock price, high idiosyncratic return volatility, and high idiosyncratic return skewness.[3] In addition to using each of the three measures independently, we also form a composite lottery-feature index that incorporates all three features. We show that stocks with strong lottery features significantly outperform their counterparts in January; in other months such outperformance is attenuated and commonly reversed.

Over the 44 January months from 1964 through 2007, an equal-weighted (value-weighted) hedge portfolio that is long the highest lottery-feature index quintile and short the lowest index quintile generates a mean January return of 11.48% (7.21%), and a monthly Fama-French three-factor alpha of 8.51% (4.13%). The equal-weighted portfolio has only one negative January return over this period. The January outperformance of lottery-type stocks is robust to adjustments for the bid-ask-spread (Keim 1989), the delisting bias (Shumway 1997), the elimination of stocks trading below $5, and controls for the January effects in firm size, book-to-market equity, past short and long run returns, and loadings on a set of common factors. The effect is concentrated within a 20-day window surrounding New Year's Day and cannot be fully explained by tax-loss selling, institutional window-dressing and risk-shifting. Additionally, Lottery-type stocks are demanded by both individuals and institutions in the New Year and deliver low expected returns for the remainder of the year. However, only those purchased by individuals earn negative subsequent returns, suggesting individual investors paying a bigger premium that results in negative payoffs in lottery-type stocks. This is consistent with the finding by Kumar (2009) that retail investors exhibit stronger gambling preference than institutional investors in portfolio allocation.

In the China stock markets, we examine whether gambling mentality impacts stock returns in the New Year, but not necessarily in January unless the two coincide. This is important for clearly distinguishing the gambling-preference-based hypothesis from traditional hypotheses for broad January effects that involve tax-loss-selling (Ritter 1988; Starks, Yong, and Zheng 2006), institutional

[3] Kumar (2008) suggests that investors begin searching for lottery-type stocks among those with low prices and then examine those with high skewness. High return skewness indicates a small probability of winning a large "jackpot," while high return volatility likely inflates the perception of the likelihood that the extremely large payoff is paid.

window-dressing (Haugen and Lakonishok 1992), or institutional risk-shifting (Ng and Wang 2004). Chinese stock markets provide an ideal setting to test these competing hypotheses. Chinese celebrate the traditional Chinese New Year's Day based on the lunar calendar, also known as the "Spring Festival," more seriously than January 1st.[4] Chinese have a tradition of gambling in the New Year. There is no income or capital gains tax imposed on stock trading and an overwhelming majority of investors are retail.[5] Both the tax-loss-selling or institutional-trading-based hypotheses would predict no January or New Year effect. In contrast, the gambling-preference-based hypothesis predicts that the Chinese market as a whole and the lottery-type Chinese stocks outperform at the start of the Chinese New Year, but not necessarily in January. We find strong evidence for the two gambling-based predictions.

Our hypotheses and findings provide unique insights into a set of long-standing phenomena related to the January effect in stock/bond returns (Rozeff and Kinney 1976). The predominate explanation for the January effect is tax-loss selling. But, the January effect is found in countries or time periods with no capital gains taxes (Kato and Schallheim 1985; Van den Bergh and Wessels 1985), and in countries with tax years ending in a month other than January (Gultekin and Gultekin 1983; Brown, Keim, Kleidon, and Marsh 1983). The January effect occurs for noninvestment-grade bonds but not for investment-grade bonds (Maxwell 1998). These findings fit into our interpretation based on investor gambling preference in the New Year. In our US stock sample, adding the lottery feature variables (particularly the skewness measure) in Fama-MacBeth regressions visibly reduces the magnitude of, or even reverses, the sign of the coefficients on firm size. Thus, our hypothesis provides a partial explanation for broad phenomena related to the January effect.

It is, however, important to note that our results are not simply a repackaging of existing January effects. Our lottery measures show predictive power after controlling for all other January-related firm characteristics. Lottery-type stocks do well in January from the early 80s through late 90s, a period during which the small-firm-in-January effect dissipated (Schwert 2003; Haug and Hirschey 2006). More importantly, the findings about January effects of idiosyncratic volatility and skewness, of OTM versus ATM calls, and the New Year's effect of Chinese stocks are all novel. While the

[4] The Chinese Spring Festival is a single day and equivalent to the US New Year's Day. It is based on the lunar calendar and usually occurs somewhere from mid-January to mid-February, depending on the year.

[5] Chinese stock investors only pay a stamp tax for each stock transaction. In 1998 mutual funds held only 2% of the Chinese tradable A-shares and in March of 2006, their holdings rose to 14.4%. This explosive growth, however, occurs only after 2003 when the first national Law on Securities Investment Funds went into effect (Xi 2006).

gambling-preference-based hypothesis provides a coherent story for our results, these findings are interesting empirical facts irrespective of the interpretation.

The remainder of this paper is organized as follows. Section 2 summarizes the motivational literature. Section 3 describes the data. Section 4 presents the empirical results from US option and stock markets and China stock markets. Section 5 summarizes and concludes.

2. Motivation and Hypotheses

2.1. Gambling Preference and Asset Prices

The notion that individuals have a preference to speculate with part of their wealth emerged over 50 years ago. Both Friedman and Savage (1948) and Markowitz (1952) point out that it is puzzling that individuals often buy insurance as well as lotteries. They raise the question of why individuals exhibit both risk-aversion and risk-seeking behaviors.

Behavioral portfolio theory developed by Shefrin and Statman (2000) suggests one possibility. Under this theory, investors view financial assets as pyramids; they purchase insurance for downside protection, diversified mutual funds to ensure their current social rank, and securities with speculative features for an upside potential. Based on the level of investor aspirations to move upward in social class, they can choose aggressive individual stocks, call options, or lotteries. Therefore, the preference to gamble is not caused by risk seeking, but by aspiration.

Alternative theoretical work suggests other reasons for the preference to gamble. For instance, Barberis and Huang (2008) suggest that investors are willing to pay for skewness because they overestimate the probability of extremely rare events, which is an aspect of prospect theory (Kahneman and Tversky 1979). Brunnermeier, Gollier, and Parker (2007) model the preference for skewness as an outcome of investors being overly optimistic about the probability of good states. In the model of Mitton and Vorkink (2007), investors have heterogeneous preferences for skewness. The above models all conclude that the preference for skewness impacts equilibrium prices; securities with speculative features are overpriced and thus deliver lower expected returns.

The theoretical approach of gambling preference helps to explain a range of stock market phenomena, including IPO underperformance (Loughran and Ritter 1995), investor underdiversification (Goetzmann and Kumar 2008), pricing of OTM options (Bollen and Whaley 2004), diversification discounts (Lang and Stulz 1994), and underperformance of high idiosyncratic volatility securities

(Ang, Hodrick, Xing, and Zhang 2006).

Kumar (2009) shows that lottery-type stocks are overweighted in portfolios of retail investors but not in those of institutional investors. Zhang (2005) and Boyer, Mitton, and Vorkink (2008) show that measures of expected skewness of idiosyncratic stock returns are negatively related to future stock returns, supporting the prediction that highly skewed stocks are overpriced due to investor preferences for skewness. Our paper is most related to the above research. We find that high idiosyncratic skewness stocks outperform in January but underperform in other months, suggesting that overpricing of highly skewed stocks largely occurs in January and is corrected in the remaining months of the year. We also go beyond the above empirical literature by studying the gambling-preference-induced seasonality in option markets and Chinese stock markets.

2.2. Gambling Preference and the Turn-of-the-New-Year

Experimental evidence from psychology and financial decision making suggests that investors may exhibit different behavior at the turn of the New Year. For instance, individuals tend to change their risk-taking tendency when decisions are framed in a multi-period setting. Thaler and Johnson (1990) show that after experiencing prior gains in a lottery play, individuals become more risk seeking in subsequent plays; this is termed the "house money effect". After experiencing losses but being offered a chance to break even, individuals are also more willing to gamble; this is termed the "break-even effect." One possible explanation is that multiple-period financial decisions are evaluated and labeled in intertemporal mental accounts (Thaler 1985), in which outcome payoffs from last period affect risk-taking in this period.[6] If the turn-of-the-year is the starting point for the new round of gambling/investing, we expect that shifts in risk-taking occur more frequently at the start of the New Year.

[INSERT TABLE 1 HERE]

Anecdotal evidence suggests that people tend to actively engage in gambling for the New Year. Table 1 provides an incomplete list of recent press articles that show such New Year's gambling mentality exists in the US and worldwide. Many states in the US offer New Year's Eve (Millionaire) lottery raffles with the largest prize $1 million and the winners drawn around New Year's Eve. A recent article reports that "(New Year's Eve) raffle games have become popular in recent years in

[6]See evidence by Weber and Camerer (1998) and Arkes, Hirshleifer, Jiang, and Lim (2008).

the United States."[7]

The typical seasonality in Las Vegas gambling, reported in the press, is also consistent with a gambling mentality in the New Year. For instance, it is said that "the period between Superbowl Sunday and the Chinese New Year is traditionally a lucrative one for Las Vegas: first, as US sports enthusiasts flock to the Strip to bet on the game; and later, as ethnic Chinese and other Asian high rollers fly in to test their luck during the lunar new year... About 20 percent of yearly baccarat volume — a card game that is a key measure of high-end play, occurs in January and February..."[8]

The mentality to gamble in the New Year is reported in countries like Greece, Turkey, and China, where people commonly engage in gambling activities to celebrate the New Year. For instance, Chinese traditionally play games like "Mahjong" and visit casinos. Greeks usually gamble on New Year's Eve, and New Year's gambling is big business in Greece. In New Zealand, Christmas is the busiest time of the year for casinos nation-wide. In Turkey, the national lottery runs a special drawing every Dec. 31st for the New Year. "The hype surrounding the Dec. 31 jackpot is a normalized part of Turkish culture surrounding New Year's."[9]

[INSERT FIGURE 1 HERE]

To formally analyze the seasonality in gambling, we study the gaming revenues from the Las Vegas Strip, which is ranked the largest location of US casinos in terms of annual gaming revenue in 2007 by the American Gaming Association. The gaming revenue data come from the State of Nevada Gaming Control Board (gaming.nv.gov) over the period 1996–2007. The visitor statistics come from the Las Vegas Convention and Visitors Authority (www.lvcva.com), and the number of local residents is from the US Census Bureau.

In Panel A of Figure 1, we plot the average dollar gamed per visitor on the Strip between January and other months from 1997–2007. The per capita gaming revenue is defined as the total gaming revenue from the Strip divided by the number of visitors, which helps adjust for the tourism seasonality in Las Vegas visitation. It is clear that the per visitor gaming revenue is higher

[7] Sources: "New Year's Eve lottery raffles from around the USA," Lotterypost.com, January 1, 2008. In 2008, the states that offer the New Year's Eve lottery raffles include Arizona, California, Delaware, Florida, Georgia, Idaho, North Carolina, New Jersey, New Mexico, Ohio, Pennsylvania, South Dakota, and Virginia.

[8] Source: "Las Vegas looks for a change in fortunes," by Mariko Sanchanta, *Financial Times*, February, 2002. Note that baccarat is unrelated to the gambling on the Superbowl, so the January mentality in Las Vegas is not unique to sports gaming. For instance, "March Madness", which refers to gambling on college basketball, occurs in March. But we find no significant increase in gaming revenue on Las Vegas for that month.

[9] Source: "Turks dream of big money as New Year's Eve approaches," by Roberta Davenport, December 14, 2008, http://www.sundayszaman.com.

in January than other months for all years. On average, a visitor gambles \$159.50 in January and \$140.32 per month in all other months with an average difference of \$19.18 ($t = 5.42$), or 14% more in January.[10]

Panel B further shows that the gaming activity is highest in January, regardless of whether the per capita gaming revenue is adjusted for the total population or total number of visitors. The high gaming activity in January is not caused by a larger number of gamblers in this month. In fact, there is little variation in the number of visitors to Las Vegas each month. The percentage of visitors in January is neither the highest nor the lowest among the months and visitors consist of a fairly stable fraction of the total population across all months. Therefore, the intensive gambling activity on the Las Vegas Strip is not driven by seasonality in visitation.[11] Therefore, the evidence suggests a stronger gambling mentality around the New Year. Since regular casino gamblers possess similar demographic profiles to typical lottery players (Campbell and Ponting 1984; Hinch and Walker 2005) who, in turn, are demographically similar to investors that prefer lottery-type stocks Kumar (2009), we expect that the mentality of casino gamblers reflects that of lottery-type asset players in the financial markets.

2.3. Hypotheses

In sum, theoretical models suggest that investor gambling preference can impact equilibrium asset prices. Anecdotal evidence, research in individual risk taking, and our Las Vegas data suggest that investors exhibit stronger gambling preferences at the turn-of-the-new-year. Thus, we expect securities with lottery features to outperform at this time as a result of investor excess demand. We examine this hypothesis using US options and stocks, and Chinese stocks. We lay out the testable hypotheses below.

In the US option markets, we hypothesize that investors demand OTM more than ATM call options in January to a greater extent than during other months of the year. This is due to the speculative feature associated with OTM calls. We assess the price impact through measuring the

[10] Since the number of visitors is fairly stable throughout the year, the total gaming revenue is also the highest in January. In other words, at both the individual and the aggregate level, gambling mentality appears to be strongest at the-turn-of-the-year.

[11] The International Consumer Electronic Show is hosted in January and tends to have the largest number of attendees among all conventions in Las Vegas. Since the number of visitors is similar across all months. This implies that less people visit Las Vegas in January for the sole purpose of gambling. Thus, the gaming revenue per gambler should be even higher in January than in other months.

implied volatility spread between OTM and ATM calls. We assess the volume impact through the trading volume spread between the two.

> **H1a:** The implied volatility spread and trading volume spread between OTM and ATM call options should be greater in January than in other months.

In addition, we expect a stronger shift towards lottery-type bets among small investors (customers) than among large institutions (firms) as evidenced by more calls relative to puts purchased in January than in other months.

> **H1b:** Individual investors, particularly small ones, should have higher call/put open buy ratios than institutions in January than in other months.

Since we do not have data on the moneyness of the options purchased through the customer and firm accounts, we infer the moneyness by the average premium per option of each account type. We expect that customers purchase cheaper options than firms do, especially in January. Given the stock, a lower option premium implies that the option is more out-of-the-money. However, given the moneyness, a lower option premium is associated with a lower price of the underlying security. In both cases, the implication of a lower option premium suggests that investors favor lottery-type assets (either stock or options, or both).

> **H1c:** Customers, particularly small ones, should buy relatively cheaper options than firms, and particularly so in January than in other months.

In the US stock market, we examine the cross-sectional stock return patterns across lottery features between January and other months.

> **H2:** Stocks with strong lottery features (low price, high idiosyncratic volatility, high idiosyncratic skewness) should outperform those with weak lottery features in January, but not necessarily in other months.

We also provide tests to distinguish the gambling-preference-based hypothesis from traditional hypotheses involving individual tax-loss selling, institutional window-dressing, or institutional risk-shifting.[12] The traditional hypotheses predict that the January effect of lottery-type stocks should occur solely for past losers or for stocks bought by institutions. However, the gambling-preference-based hypothesis predicts that it should occur regardless of the past returns and institutional trading.

> **H2a:** The outperformance of lottery-type stocks should be present among both past winner and loser stocks, and among stocks that are net bought as well as net sold by institutions.

To gather additional evidence for the New Year's gambling mentality, we also examine whether the January outperformance of lottery-type stocks is concentrated around New Year's Day.

> **H2b:** The outperformance of lottery-type stocks should be stronger in trading days surrounding New Year's Day than other trading days later in January.

We further hypothesize that individual investors should exhibit stronger speculating preferences toward lottery-type stocks than institutional investors do. As a result, the lottery-type stocks selected by individuals, like lotteries, should deliver lower expected returns than those selected by institutions.

> **H2c:** For lottery stocks purchased at the beginning of the year, subsequent underperformance from February through December should be stronger if purchased by individuals than if purchsed by institutions.

In the China stock markets, we focus on the comparison between Chinese New Year months and January trading days that precede the Chinese New Year's Day. We examine the market as a whole and the relative performance between lottery-type Chinese stocks and their counterparts.

> **H3a:** Chinese stock markets as a whole should outperform in the Chinese New Year month, but not necessarily in January.

[12] Tax-loss selling refers to investors' tendency to realize capital losses at the end of the year and repurchase the securities in January. Window dressing refers to institutions' tendency to sell loser stocks at the end of the year to avoid reporting those holdings to shareholders. Risk shifting involves the temporary institutional purchase of risky stocks in January since managers' compensation is tied to the performance of the managing funds relative to a benchmark. These traditional hypotheses predict that only past loser stocks or stocks net bought by institutions should outperform in January. For recent research on these effects see Poterba and Weisbenner (2001), Ivkovic, Poterba, and Weisbenner (2005), and Starks, Yong, and Zheng (2006).

H3b: Chinese stocks with strong lottery features should outperform those with weak lottery features in the Chinese New Year month, but not necessarily in January.

3. Data and measures of lottery features

3.1. Data

Our US stock sample includes all common stocks (share codes 10 and 11) listed on the NYSE, AMEX, and NASDAQ from July 1963 through December 2007. Stock returns and other trading data are obtained from the Center for Research in Securities Prices (CRSP). Accounting information for the calculation of book equity is from COMPUSTAT. Institutional ownership data are from the Thomas Financial 13F file over the period 1980–2007. Implied volatility from call options and volume data are from OptionMetrics from 1996–2006. The call and put option volume data for different categories of investors are obtained from the Option Clearing Corporation (OCC) from 2000–2008. Chinese stock market data are from DataStream over the period 1993–2006. We obtain the Fama and French factor returns from Kenneth French's website.

3.2. US option moneyness and open buy volume

For a firm's options to be included in the sample they must have non-zero trading volume for at least one ATM and one OTM call option for contracts expiring in the following month. We define OTM calls as the ratio of the strike price to the stock price greater than 1.05 and ATM calls as having the same ratio between 0.975 and 1.025. The implied volatility is measured on the last trading day of each month for options that expire in the following month. We compute the average implied volatility separately for all OTM and ATM calls for each stock. Then we define the monthly implied volatility spread (OTM−ATM) as the mean difference between OTM and ATM implied volatilities across all stocks in a given month.

For each call option, monthly volume is the sum of daily volume. To capture the aggregate monthly volume, we define the option volume of OTM (ATM) calls as the total monthly trading volume across all OTM (ATM) calls in a given month. Since option volume on average follows an upward time trend, we separately compute for OTM and ATM calls the percentage change of the current month option volume from its past 12-month moving average, and we label it as adjusted option volume. Then we calculate the monthly adjusted volume spread (OTM−ATM) as the average difference between the adjusted option volume of OTM calls and that of ATM calls.[13]

Since we are also interested in who is buying options, we use information from weekly OCC volume reports, which separate open call and put buys and sells of equity-based options by firm, customer, and market maker. Open buys refer to new purchases of options and do not include buying to cover previous short option positions. The OCC reports include weekly aggregate transactions across all exchanges, strike prices, and maturities for each account type. We focus on the first two account types, where a "firm" account refers to an account established by a clearing member carried on for the purposes of the clearing member, and a "customer" account refers to an account established by a clearing member on behalf of its customers. The clearing members tend to be large institutions while customers include retail investors as well as non-clearing member institutions (such as small hedge funds).

Based on the size of each transaction, customers are further classified into three groups: 1-10 contracts per transaction, 11-49, and above 50. Following (Battalio, Hatch, and Jennings 2004), we use the group with 1-10 contracts per transaction, which we refer to as small customers, as a proxy for retail orders. Based on whether the Friday of a week is in January, we classify the weeks as January and non-January. We are interested in whether more open calls, relative to open puts, are bought in January weeks for all types of investors, and whether this open buy call/put ratio is highest for customers, particularly for small customers, versus firms. To study the relative cost of options, we define the call (put) premium per option as the dollar amount of premium paid over the number of open buy call (put) contracts times 100. We expect that, on average, customers (especially small ones) pay a smaller premium than firms, and particularly in January.

3.3. US stock lottery feature measures

For the US sample, we use three measures of stock lottery features. The first is stock price (PRC), the closing price at the end of the immediately preceding month. Like lotteries, lottery-type stocks should be cheap. The second is idiosyncratic volatility (IVOL). High idiosyncratic volatility inflates the perception of the chance to realize high returns, thus attracting stock market

[13] A potential concern is that for a given month, the OTM options have a higher or lower strike to stock ratio than other months, resulting in comparing the implied volatility or volume at different points on the volatility skew. However, we find that the average OTM strike/spot ratio for the sample is 1.17, and there are no significant differences across the individual months. The lowest is 1.16 (August) and the highest is 1.19 (April). For ATM strike/spot ratios, the average for the sample and the months is 0.999.

gamblers. Following Ang, Hodrick, Xing, and Zhang (2006), IVOL is defined as the standard deviation of at least 17 daily residual returns within the preceding month, where residual returns are estimated from the Fama and French (1993) three-factor model. Our main findings for January hold for a number of alternative measures of firm-specific volatility, including idiosyncratic volatility estimated from either the past 3-month daily or 12-month weekly returns, the implied idiosyncratic volatility inferred from option prices, and idiosyncratic volatility from an EGARCH model. Part A of the appendix presents the details to construct these measures and the corresponding results.

The third lottery feature is idiosyncratic skewness. Skewness gauges the potential size of the "jackpot" that comes with a very small probability. The definition of lottery-type stocks suggests that investors care about the expected, not the realized, return skewness. Prior literature shows that future skewness is poorly predicted from past skewness; thus it is important to estimate expected, not realized, idiosyncratic skewness (Zhang 2005; Boyer, Mitton, and Vorkink 2008). We employ the approach of Boyer, Mitton, and Vorkink (2008) that uses a set of firm characteristics to forecast future idiosyncratic skewness through monthly cross-sectional regressions.

Specifically, for each individual stock we first calculate realized idiosyncratic skewness (ISKEW) based on at least 26 out of 52 weekly residual returns over a rolling 12-month window. The residual returns are estimated from regressions of weekly stock returns on weekly market returns and squared weekly market returns (Harvey and Siddique 2000; Kumar 2009).[14] Then we run month-by-month cross-sectional firm-level regressions. The dependent variable is the future 12-month realized ISKEW measured from month t. The independent variables include the past 12-month ISKEW value and a set of other firm characteristics suggested by Boyer et al. (2008). To obtain the expected idiosyncratic skewness (EISKEW), we apply the regression coefficients estimated in month $t-12$ on independent variables observed in month $t-1$. For example, in December of 1997 we use the coefficients estimated in December of 1996 and the skewness predictors measured as of December of 1997 to compute EISKEW. Then we use EISKEW to forecast stock returns in January of 1998. In other words, EISKEW is computed with prior information and used to forecast future returns. Our main results are insensitive to alternative specifications to forecast EISKEW. Part B of the appendix presents the robustness checks that are based on five alternative specifications.

[14] Our results hold if the residual returns are estimated from the Fama-French three-factor model, and if the rolling window is three or six months long. We focus on the 12-month measures because our hypothesis implies that investors buy lottery-type stocks in January for a chance of a "home run" in the year.

We also construct a lottery-feature index (LOTT) that incorporates PRC, IVOL, and EISKEW. The purpose is to consolidate reporting results, although our main findings hold for each of the lottery features. To construct the lottery-feature index, we independently rank all stocks into 20 groups for each lottery measure. Then we assign a ranking to each of the three sets of portfolios with the highest ranking, 19, assigned to the lowest PRC, highest IVOL and highest EISKEW portfolios, and the lowest ranking, 0, assigned to the other three extreme portfolios. The portfolio rankings are assigned to each stock included in the portfolio. For each stock we define the average of the three rankings as the lottery feature index LOTT.[15]

3.4. China stock lottery feature measures

For the China stock sample, we measure lottery features with logarithmic price (LOGPRC) and idiosyncratic volatility (IVOL). We forgo the expected idiosyncratic skewness because many firm characteristic variables are unavailable. Stock price, in local currency, is measured at the end of the preceding month. Idiosyncratic volatility is the standard deviation of residual returns from a regression of at least 15 daily returns in the preceding month on contemporaneous daily returns on the Shanghai and the Shenzhen (two major exchanges in China) index returns. Sometimes in January and March the number of trading days for the overall market is less than 15. This occurs when the Chinese New Year's Day is in early January or late February. If this happens IVOL of month $t-2$ is used to forecast returns for month t. Stock returns are also measured in local currency.

Since the Chinese New Year's Day can occur anywhere from January to February, we define January, the Chinese New Year month, and March as including January trading days prior to the Chinese New Year's Day, the 22-trading-day period following the Chinese New Year's Day, and the subsequent trading days through the end of March, respectively.[16] We cumulate returns over each of the re-defined months and normalize them to a 22-day period return. We also compute monthly returns from April to December. All returns are expressed on a monthly basis, with returns in January and March adjusted for the number of actual trading days. Finally, we compute the equal-

[15]To maximize the number of observations of lottery-type stocks, we only require one of the three rankings to be available to compute LOTT. However, our results hold if we require two or three rankings to compute LOTT.

[16]Since the Chinese New Year's Day tends to occur somewhere from mid-January to mid-February, our definition classifies the trading days in February preceding the Chinese New Year's Day as belonging to no group. However, our results are similar if we classify those trading days as if they occur in March, which causes the trading days defined in March to be skipped by the New Year's month in some years.

weighted monthly returns across all available stocks and use it as a proxy for the equal-weighted market portfolio.

3.5. Summary statistics

[INSERT TABLE 2 HERE]

The US option sample is described in Panel A of Table 2. The average annualized implied volatility of OTM calls is 55.32%, higher than that of ATM calls of 42.33%. The fact that implied volatility for OTM calls is higher than ATM calls is consistent with the smile behavior for individual equity options versus index options (Bakshi and Kapadia 2003). On average, OTM calls are traded less than ATM calls, and after adjusting for the time-trend in own volume, OTM calls show a smaller percentage increase than ATM calls. Additionally, the ratio of call to put buys is larger for individual customer open buy transactions than firm open buy transactions, and especially so for the smaller customer open buy transactions. The volume and call/put ratios are generally consistent with the evidence by Pan and Poteshman (2006) that are based on slightly different definitions of ATM and OTM and use a different dataset.

Panel B of Table 2 reports the summary statistics for the lottery feature measures. The average stock price is roughly \$10 ($\approx e^{2.27}$), the average daily idiosyncratic volatility is 2.96%, or 47% on an annualized basis, idiosyncratic weekly skewness is 0.62, and expected weekly idiosyncratic skewness is 0.60. The correlation matrix in Panel B shows that PRC, IVOL, and EISKEW are highly correlated, but the correlations between past skewness (ISKEW) and other lottery features are much weaker. Consistent with prior literature, the results indicate that EISKEW more accurately represents stock lottery features than past ISKEW.

Panel C describes the China stock sample. The average monthly stock return is 0.21% with a negative median return (-1.06%) and a large standard deviation (14.70%). This is because there are predominately more firms in the latter period of the sample during which China stock markets have poor performance. The average stock price in local currency is similar in magnitude to the US level. The average daily IVOL is 1.61%, which is smaller than in the US sample. This is not because China stock markets are less volatile, but because Chinese stock volatility is affected more by systematic risk rather than idiosyncratic risk. In our subsequent tests, we use cross-sectional demeaned stock returns as dependent variables. Thus, our results are not driven by certain unique periods in the sample.

[INSERT TABLE 3 HERE]

Panel A of Table 3 presents characteristics of quintiles of stocks sorted on LOTT. The average log price is 3.57 ($\approx$ \$35 per share) for the lowest LOTT quintile of stocks and 1.06 ($\approx$ \$2.88 per share) for the highest quintile. Although there are roughly equal numbers of firms (about 1000) in each quintile, their market capitalizations proportional to the overall market are quite different. The lowest LOTT quintile accounts for over 80% of the total market cap while the highest LOTT quintile accounts for merely 1%. Our subsequent tests show that the relation between lottery features and January returns is monotonic. Thus, even after we exclude the highest LOTT quintile of stocks, there still exists significant return differentials across LOTT groups.

The correlation matrix between lottery feature variables and various firm characteristics are reported in Panel B. Panel C reports the Fama and MacBeth (1973) regression coefficients that forecast EISKEW. The independent variables include LOGPRC, IVOL, ISKEW, logarithmic firm size (LOGME), logarithmic book-to-market equity (LOGBM), past one-month returns (RET(-1)), past returns from month $t-12$ through $t-2$ (RET($-12,-2$)), and share turnover in the previous month (TURN). Firm size is measured at the end of the previous month. Book-to-market equity is measured following Fama and French (1993), where the book equity with fiscal year ending in year $s-1$ and market equity at the end of December of year $s-1$ are used in the cross-sectional regression from the end of June of year s through May of year $s+1$. RET($-12,-2$) is expressed on a monthly basis. TURN is the ratio of the total number of shares traded in the previous month over shares outstanding. Due to a possible double counting of trading volume among NASDAQ firms (Atkins and Dyl 1997), we divide their trading volume by two. The forecast regression requires that all predictors are available. Thus, the total number of observations for which we have EISKEW available are reduced by about 25% from those with ISKEW.[17] All coefficients are statistically significant and their signs are consistent with those in Boyer, Mitton, and Vorkink (2008).

[17]Depending on the specification, the reduction of the number of available firms can be less. The appendix shows alternative specifications that require fewer predictors and, hence, have more firm-month observations. Our main results hold for these samples too.

4. Empirical Results

4.1. US option markets

4.1.1. Implied volatility and volume spreads

For our option sample, we examine option pricing and trading. We test Hypothesis H1a that the implied volatility spread (which is inferred from call option prices and measures the relative expensiveness of options) and trading volume spread between OTM and ATM calls should be greater in January than other months.

[INSERT TABLE 4 HERE]

Panel A of Table 4 reports the month-by-month average implied volatility spread of OTM and ATM calls over the period 1996–2006. Consistent with our conjecture, the implied volatility spread is higher in January than other months, suggesting that OTM calls are relatively most expensive in the New Year. The average difference of the annualized implied volatility spread between January and other months is 4% and statistically significant ($t = 5.55$).

Panel B of Table 4 reports the adjusted option volume spread from January through December. As expected, the adjusted volume spread is higher in January than other months. The average difference in the adjusted volume spread is 0.29 between January and non-January months, which is statistically significant ($t = 2.09$). That is, relative to ATM calls, OTM calls are traded most in January. Thus, our evidence supports Hypothesis H1a that there is excess demand for OTM calls at the turn of the year.

4.1.2. OCC open buy call/put ratios, call and put premiums

[INSERT TABLE 5 HERE]

To test Hypothesis H1b, we examine the seasonality in customers' call/put open buy ratios versus those for firms. Panel A of Table 5 shows the average call/put open buy ratios for January and all other months. The results show two findings consistent with our hypothesis. First, the open buys of calls, relative to puts, is higher in January for both customers and firms than in other months. Second, the average customer open buy call/put ratio is significantly higher than that of the firm in January. This is especially true for customer purchases of between 1 and 10 contracts. The difference in the ratios is 1.14 with a t-statistic of 5.50. So while both firms and customers purchase more calls in January, smaller customers are much more inclined to buy calls relative to puts in January.

To test Hypothesis H1c, we examine separately for calls and puts the premium per option in the open buy transactions for firm and customer accounts. Panel B reports the call premium for January and non-January months. On average, customers pay lower premiums than firms, regardless of the month when the transaction occurs. This suggests a possible preference of customers toward cheap bets in the equity market, a behavior that is consistent with the gambling-preference-based hypothesis in general. We also find that all investors tend to pay higher premium in January than in other months, which is consistent with our results about the implied volatility in Table 4 (OTM options are more expensive in January). Relative to firms, however, in January the increase in premium paid by customers is significantly smaller than that paid by firms. This is evident in a negative mean of $(\text{Customer}-\text{Firm})_{\text{Jan}-\text{NonJan}}$ for all customers; all of these differences are significant at the 5% level. This suggests that, in January, customers shift toward options that are more out-of the-money or options with even lower-priced underlying. In contrast, we do not observe a similar pattern in January for put premium. As reported in Panel C, there is not significant differences in the change in premium in January for customers versus firms. Both evidence from calls and puts suggests that investors tend to gamble through purchasing OTM call options. Overall, our evidence from the US option markets provide direct support to our hypothesis that investors demand lottery-type assets and impact asset prices and volume.

4.2. US stock sample

4.2.1. Sorts

We now test Hypothesis H2 about whether lottery-type stocks outperform those with opposite characteristics mainly in January.

January versus Non-January Months

Each month we independently sort stocks into quintiles based on the three lottery feature variables PRC, IVOL, and EISKEW, and the lottery feature index LOTT. We then compute the average value- and equal-weighted returns of each quintile for the subsequent month. We form hedge portfolios (S−W) that are long the strongest lottery feature (low PRC, high IVOL, EISKEW, and LOTT) and short the weakest lottery feature quintiles and compute mean returns and alphas from the Fama and French (1993) three-factor model for these portfolios. Our results are similar if we add the momentum factor to the three-factor model. We start by examining the relation between lottery features and stock returns across all months. The purpose is to replicate prior results using the most recent sample and set the benchmark for separating January analyses from other months.

[INSERT TABLE 6 HERE]

As shown in Table 6, the average relation between lottery features and stock returns across all months is mixed. With value-weighted portfolio returns we find that low PRC, high IVOL, and high LOTT stocks tend to underperform their counterparts, controlling for the Fama-French three factors. In particular, the highest value-weighted IVOL quintile underperforms the lowest by 0.97% per month ($t = -3.02$), similar in magnitude to the 1.06% found by Ang, Hodrick, Xing, and Zhang (2006) over the period 1963–2000. Using equal-weighted returns, however, this relative underperformance of lottery-type stocks diminishes,, consistent with Bali and Cakici (2008). Additionally, the equal-weighted raw returns on the hedge portfolios are mixed in sign and none of the alphas are statistically significant at the 5% level. Across all months, whether lottery-type stocks under- or overperform appears sensitive to the portfolio weighting scheme.

We next separate January returns from those of other months. Our hypothesis H2 predicts that there should be a positive relation between lottery features and stock returns in January. The monthly separation shows that January returns across lottery features differ sharply from the non-January return patterns. For all four lottery features, and for both equal- and value-weighted returns, there is a strong positive relation between lottery features and stock returns. The hedge portfolios based on PRC, IVOL, ESIKEW, and LOTT produce average January returns of 3.91–13.15%. All January alphas but one are statistically significant at the 1% level. In contrast, in non-January months there is a consistent negative relation between lottery features and portfolio returns across all lottery features. All alphas are negative and statistically significant at the 5% level or better.

In other words, there are opposite relations between lottery features and portfolio returns across January and non-January months. The positive relation in January is consistent with our hypothesis that investor preference for lottery-type stocks impacts returns at the turn of the year. The negative relation in non-January months, consistent with behavioral models (Barberis and Huang 2008; Mitton and Vorkink 2007; Barberis and Xiong 2008), suggests a correction of overpricing of lottery-type stocks caused by investor preference for speculative features. Our findings also show that the

January effect of lottery-type stocks is responsible for the difference in return patterns between equal- and value-weighted portfolios. If Januarys are excluded there is a consistent negative relation between IVOL/EISKEW and stock returns, regardless of the weighting scheme.

Month-by-Month Returns

It is possible that lottery-type stocks also outperform in months other than January, such as at the quarter-end. For instance, if institutional risk-shifting occurs at the turn-of-the-quarter and it is responsible for the high returns of lottery-type stocks, then lottery-type stocks would outperform in January, April, July, and October. If true, our analysis that combines all non-January months would disguise the quarter-end seasonality.

[INSERT TABLE 7 HERE]

To examine the quarter-end or other possible calendar effects, in Table 7 we report the mean value- and equal-weighted long minus short portfolio returns from January through December. Similar to Table 6, the long-short portfolio is long the quintile with the strongest lottery features and short the one with the weakest features. Consistent with our hypothesis, lottery-type stocks significantly outperform in January, slightly outperform in February, and tend to underperform in the remaining months. Using LOTT, in February the long-short value-weighted return is 0.16% ($t = 0.19$) and the equal-weighted return is 1.30% ($t = 1.59$). From March through December the long-short LOTT returns are all negative except in May for the equal-weighted return. There is, however, no evidence for quarter-end effects.

4.2.2. The January trading strategy

Is the lottery-stock-in-January effect exploitable? We examine the implications of our results for trading strategies for two reasons. First, it is important to understand whether our results have value for practitioners. Second, it is useful to see whether any trading profits survive microstructure considerations, such as the bid-ask spread.

[INSERT FIGURE 2 HERE]

We consider the equal-weighted hedge portfolios based on the LOTT quintiles that are formed at the end of each December and liquidated at the end of the following January. We focus on equal-weighted returns because Table 6 shows that the equal-weighted hedge portfolios deliver higher expected returns than value-weighted ones. Thus, it should be a more attractive investment strategy and deserves a more careful examination.

In Panel A of Figure 2 we present an annual display of the January returns over the 44 years from 1964 through 2007. The mean raw return of 10.40% per month is earned with only one yearly loss, in 2005 (−6.04%). The highest profit year is 2001 with a remarkable 72% January return. Overall, high returns seem to come with limited downside risk.[18] An investor who starts in 1965 with one dollar in the hedge portfolio and invests from the end-of-December to the end-of-January would end up with over $92.84 by the end of January of 2007. By contrast, those who trade in the opposite direction would virtually lose all of their investment (with less than 1 cent left for every dollar invested).

One possible concern is that the long-short portfolio return is an artifact due to substantial bid-ask spread in low-price stocks (Keim 1989; Conrad and Kaul 1993). Keim suggests that there is a systematic shift of the closing price from at the bid in December to at the ask in January, artificially inflating returns, particularly on low-price stocks. Thus, it is important to assess whether the outperformance of lottery-type stocks persists after accounting for the spread.

To obtain an estimate of the bid-ask spread across a 44-year period, we use the Roll (1984) method to compute the effective percentage bid-ask spread (ROLL). It is defined as the square root of the negative autocovariance of weekly returns from February to November of the prior year, multiplied by 200. Our estimate of the mean value of ROLL is 2.79% for the lowest LOTT quintile and 8.02% for the highest LOTT quintile. For around two-thirds of our stocks we obtain a negative autocovariance for which we compute a positive implied bid-ask spread. For the remaining stocks that have positive autocovariances (which imply negative bid-ask spreads), we assume the bid-ask spread equals the mean ROLL of the quintile for a given month. This adjustment tends to overestimate the impact of the bid-ask spread and, hence, yields a conservative measure of our trading profits.[19] In Panel C we display the equal-weighted ROLL-adjusted January returns for the long-short LOTT portfolio. By definition the spread-adjusted returns are smaller than the raw returns, but clearly the superior performance of high LOTT stocks remains and they still have

[18] The impact of short-sale constraints is relatively minor here because the short position contains high price (mostly large firms) and low volatility stocks, which are generally easy and cheap to sell short.

[19] ROLL is particularly useful since the ISSM and The Trade and Quote (TAQ) data are unavailable before 1983. In unreported analyses we compare ROLL with the relative bid-ask spread, defined as the average quoted bid-ask spread over the midpoint of the stock price. The relative bid-ask spread is computed from TAQ data January quotes over the period 1983–2005. We find that ROLL tends to overestimate the bid-ask spread by 20 to 100 percent, particularly among low-price stocks. In other words, using ROLL is likely to underestimate the returns that are net of the actual bid-ask spread.

relatively limited risk. Few years have negative returns and when they occur the losses tend to be small. The average net return is 6.42% ($t = 3.69$), which remains economically significant.

Another concern is that the long-short strategy may be difficult to implement by institutions due to large indirect costs in trading low-price, highly volatile stocks (Keim and Madhavan 1998). To address this concern, in Panels B and D we plot the annual January returns for the long-short LOTT portfolio that is implemented among stocks trading for $5 or more. There are a few more years with negative returns, but tend to be small. On average, the long-short return is 4.30% ($t = 5.45$) before and 1.65% ($t = 2.17$) after adjusting for ROLL, again suggesting non-negligible profits to arbitrage by institutions.

Finally, we consider the impact of the delisting bias on our results. Shumway (1997) shows that correct delisting returns for stocks delisted for negative reasons are often unavailable on CRSP, causing an upward bias in computed returns. This can be important since our long position loads on low-price stocks that are most likely to be delisted. Thus, we check the percentage of firms in the highest LOTT quintile that are delisted in January. Over our sample period the average January delisting rate is below 0.3%. The implied impact on quintile returns is modest. Even if we replace the missing delisting returns with −100%, the reduction in returns of the highest LOTT quintile is merely 0.3%, leading to little impact on returns.

4.2.3. **Multivariate regression**

So far our evidence is consistent with the hypothesis that investor gambling preference impacts returns of lottery-type stocks in January. Next, we consider alternative explanations to our findings.

First, it is possible that our findings are driven by the January price effect. Prior research suggests that low-price stocks outperform high-price stocks in January and largely drive the small-firm-in-January effect (Keim 1983; Kross 1985; Bhardwaj and Brooks 1992). This January price/size effect is consistent with our conjecture that investor preference for lottery-type stocks drives the outperformance of low-price stocks in January. However, prior literature attributes the January outperformance of low-price stocks to either the shift in closing price from the bid to the ask Keim (1989) or tax-loss selling (Conrad and Kaul 1993). Since price or firm size is negatively correlated with idiosyncratic volatility and skewness, high volatility or high skewness stocks may appear to outperform simply because low-price/small stocks outperform in January. To rule out this alternative explanation, we examine whether IVOL and EISKEW have incremental power to forecast January returns after considering the roles of stock price and firm size.

Second, our finding can also possibly be driven by other known January seasonality in stock returns. For example, the long-term reversal effect is most pronounced (Conrad and Kaul 1993; Loughran and Ritter 1996) and the short-run momentum effect is reversed (Jegadeesh and Titman 1993; Jegadeesh and Titman 2001) in January. It is possible that the lottery-stock-in-January effect simply manifests the above known patterns. Therefore, we examine whether our lottery feature variables incrementally forecast January returns relative to past returns at different horizons.

We employ firm-level Fama-MacBeth regressions to examine the above two alternative hypotheses. Using an approach based on portfolio returns, we obtain qualitatively similar results. For brevity, the portfolio-based results are unreported but available upon request.

[INSERT TABLE 8 HERE]

In Panel A of Table 8, we report the results of firm-level Fama-MacBeth regressions. The dependent variable is January stock returns. The independent variables are a set of controls including LOGME, LOGBM, RET(-1), RET($-12, -2$), RET($-36, -13$), and the loadings on the Fama-French three factors: the market beta (β_{MKT}), SMB loading (β_{SMB}), and HML loading (β_{HML}). The first five firm characteristics are included to control for the known January seasonality associated with these variables. The factor loadings are included to control for systematic risk (excluding the loadings does not change the results). We include each of the lottery feature measures alone and with these controls, one at a time, to examine whether the lottery-stock-in-January effect is distinct from known January effects. We also include IVOL and EISKEW in addition to PRC and these controls to examine whether the lottery-stock-in-January effect is merely a January price effect.

The Fama-MacBeth regression results, reported in Panel A of Table 8, give strong support to our hypothesis. They show that the lottery feature measures forecast firm-level January returns alone and after controlling for the set of standard firm characteristics. When used alone, all four lottery feature measures significantly forecast returns in the expected direction, negative for stock price, LOGPRC, and positive for IVOL, EISKEW, and LOTT. The coefficient on LOTT is 0.812 ($t = 5.92$). Considering that LOTT ranges from 0 to 19, a change from the lowest to the highest ranking increases the mean January stock return by over 16%. Each of the four lottery feature measures remains statistically significant when we control for the set of standard return predictors. The coefficient on LOTT, 0.312 ($t = 3.54$), is reduced by over 60%, but remains highly significant; the change from the bottom to the top LOTT ranking corresponds to a marginal effect of over 6% per January. Therefore, the outperformance of lottery-type stocks in January is incremental to previously-known January seasonality.

The results also show that the lottery-stock-in-January-effect is more than a January-price-effect. IVOL and EISKEW both remain positive and statistically significant after adding to regressions with LOGPRCE and other controls. That is, both volatility and skewness play an indispensable role in selecting lottery-type stocks. More interestingly, comparing the base specification (5) with no lottery feature variables to those with, it is clear that the coefficient on log firm size is visibly reduced in magnitude, and in some cases even reverses signs. Specifically, including LOTT, PRC, and IVOL individually reduces the coefficient of LOGME from -1.554 to -0.930, -0.164, and -1.065, respectively. Including EISKEW or the three lottery features reverses the sign of LOGME to an insignificant 0.402 and 0.130, respectively. In other words, at least part of the January size effect appears to be driven by the lottery feature, particularly the skewness effect in January.

4.2.4. **Tax-loss selling, institutional window-dressing, and risk-shifting**

We test Hypothesis H2a with Fama-MacBeth regressions. This examines whether the lottery-stock-in-January effect is driven by tax-loss selling or by window-dressing, both of which predict that high returns in January should exclusively occur to past loser stocks. We separately run Fama-MacBeth regressions for past winner and loser stocks and report the results in Panel B of Table 8, where we define winners (losers) as stocks with positive (negative) 12-month cumulative returns as of the end of December. For the two separate groups, we add each of the lottery feature variables to the set of controls used in Panel A of Table 8. All lottery feature variables remain statistically significant in both winner and loser groups, suggesting that the lottery-stock-in-January effect occurs regardless of past returns. Thus, tax-loss selling and window-dressing do not fully explain this effect. We do, however, find that this effect is stronger among losers; the coefficient on LOTT is 0.503 ($t = 5.15$) among losers and 0.350 ($t = 5.13$) among winners.

Next we test the risk-shifting hypothesis. Following Ng and Wang (2004), we separate stocks into two groups based on the change in institutional ownership over the first quarter of each year. We characterize each stock as a net buy if institutional holdings increase and no-net-buy otherwise.[20] We then run a Fama-MacBeth regression on each of the lottery feature variables together with the controls. Shown in Table 8, we find significant coefficients on the lottery feature variables: 0.479 ($t = 3.66$) among the net-buy group and 0.458 ($t = 3.35$) among the no-net-buy group. In other words, the lottery-stock-in-January effect persists even when institutions are not buying, again suggesting that individual gambling preference makes a price impact.

It is possible that lottery-type stocks outperform in January simply because they announce more favorable earnings news in January than non-lottery stocks. However, we find that stocks with the strongest lottery features tend to announce less favorable earnings news, but deliver much higher returns, than non-lottery stocks in January. The same patterns in earnings surprise persist throughout the year.[21] This is consistent with Peterson (1990), which suggests that information revelation cannot explain the broad January phenomena in stock returns.

4.2.5. **Daily return and volume surrounding New Year's Day**

So far we have focused on monthly returns. We proceed to test Hypothesis H2b by studying daily returns and trading volume surrounding New Year's Day.

[INSERT FIGURE 3 HERE]

In Panel A of Figure 3, we plot the equal-weighted average daily returns of the highest LOTT quintiles over a 40-trading-day window surrounding January 1st. The highest LOTT quintile experiences a small price run-up over three trading-days around Christmas, with a daily appreciation as high as 100 basis points. Later, it has a large price run-up over a five-day window from one-day before through four-days after New Year's Day, with a daily appreciation as high as 300 basis points in the first trading day of the New Year. The abnormal return gradually recedes until the end of January. The return effect is not solely caused by past losers or stocks bought by institutions. The high LOTT winner stocks, defined as those in the highest LOTT quintile and with positive prior

[20]Since institutions only submit 13F reports on a quarterly basis, institutional positions at the end of January are unavailable. Despite this drawback, we believe that 13F reports are the best database available for the purpose of our tests for two reasons. First, direct individual brokerage account holdings (Odean 1999) come from a limited number of brokerage firms and are usually only available for a very short sample period. Thus, they do not provide information on either the changes in total individual investor holdings, nor data over a sufficiently long period of time. Second, Ng and Wang (2004) provide evidence that the buying pressure of institutions based on 13F data is associated with the strength of the turn-of-the-year effect, which supports using quarterly holding change data to infer institutional trading behavior at the turn of the year.

[21]The results are unreported but available upon request.

12-month returns, show slightly weaker returns than generally high LOTT stocks. The IO-NBUY lottery-type stocks, defined as those in the top LOTT quintile and with decreased institutional ownership in the first quarter of the current year, depict a very similar picture as the general lottery-type stocks. By contrast, the non-lottery stocks in the lowest LOTT quintile have returns indistinguishable from zero at the turn of the year.

Trading volume surrounding New Year's Day also suggests unusual investor activity for lottery-type stocks.[22]. Panel B of Figure 3 depicts the excess turnover of the same four groups of stocks over the same 40 trading-day window as in Panel A. Excess turnover for each stock is defined as the percentage change of the daily turnover from its mean daily turnover from February through November of the previous year. The purpose of computing changes in turnover relative to the recent level is to account for the commonly found upward time trend in turnover.

Panel B shows that all groups except the non-lottery stocks have elevated turnover over the entire period. The excess turnover is especially strong for about three or four trading days immediately before New Year's Day. The daily excess turnover is up to 100%–200% for different groups of lottery-type stocks. In contrast to the lottery-type stocks, the lowest LOTT quintile of stocks experiences little abnormal turnover at the turn of the year and it is always below the other four groups. The evidence is consistent with Hypotheses H1a and H1b that the return and volume effect of lottery-type stocks is particularly strong during several days surrounding New Year's Day, and is incremental to tax-loss selling and institutional trading effects at the turn-of-the-year.

4.2.6. **Individuals versus institutions**

Next, we test hypothesis H2c, which predicts that lottery-type stocks purchased by individuals will deliver worse returns in the long-run than those bought by institutions. We track separately the top and bottom LOTT quintiles, formed at the end of the December of year $s-1$, based on whether a stock is net sold or purchased by institutions in the first quarter of year s.[23] We compute the cumulative value- and equal-weighted quintile returns from February to December of year s by keeping the composition of each quintile constant. Individual stock returns incorporate delisting returns and, in the case of a missing delisting return, we use -30% (Shumway 1997). The purpose

[22]Trading volume in NASDAQ stocks is divided by two. The results in Figure 3 remain very similar if we exclude NASDAQ stocks from the sample.

[23]We leave out those with no change in (or no) institutional ownership in the first quarter. Our results, however, are similar if we include such stocks in the group net sold by institutions.

is to measure the expected returns of lottery-type stocks that are identified at the turn of the year using the realized returns in the rest of the year after January.

[INSERT FIGURE 4]

Figure 4 depicts an interesting pattern. Consistent with the findings in Tables 6 and 7, the highest LOTT quintile substantially underperforms the lowest quintile from February through December with both value- and equal-weighted returns. Also as predicted, the underperformance of lottery-type stocks is stronger among those purchased by individuals than among those purchased by institutions. In Panel A, stocks that are net sold by institutions subsequently deliver returns as low as −9.98% (value-weighted) and −4.93% (equal-weighted) from February through December. In contrast, those that are net bought by institutions deliver relatively higher expected returns of 1.07% (value-weighted) and 2.52% (equal-weighted). But both groups of lottery-type stocks underperform the comparable non-lottery-type groups. Like playing lotteries, investors, particularly individual investors, expect to earn low or negative returns upon their purchase. The return difference in lottery-type stock purchases between the two investor groups is statistically significant at the 5% level, indicating that individual investors are significantly worse off through lottery-stock picking. The evidence further confirms our hypothesis that individual investors engage in gambling despite the expected returns are negative.

4.3. Chinese stock returns around the Chinese New Year

Finally, we examine Chinese stocks around the Chinese New Year. Chinese celebrate the Chinese New Year more seriously than January 1^{st} and have a tradition to gamble in the New Year. Thus, we hypothesize that Chinese are more likely to express their gambling preference at the turn of the Chinese New Year, rather than January 1^{st},

4.3.1. Market performance

To test Hypothesis H3a, we report the mean monthly returns on the equal-weighted market portfolio in Panel A of Table 9 for all months, Chinese New Year month (CNY), January (JAN), and all other months from March through December. Over the period 1994–2006, the average market return is highest during the Chinese New Year's month with a mean monthly return of

5.92%, and lowest during January, −1.53%, which excludes the Chinese New Year's month.[24] The mean returns are mildly positive among the remaining months. In other words, the equal-weighted Chinese stock market portfolio does not exhibit a January effect, but it does have a Chinese New Year effect.[25] This is consistent with Girardin and Liu (2005) and Hsu (2005) who find that Chinese stock markets exhibit a weak January effect. The result confirms hypothesis based on New Year's gambling mentality that the Chinese New Year affects stock returns more than the January 1st New Year.

[INSERT TABLE 9 HERE]

4.3.2. **Individual stock performance**

Next, we test Hypothesis H3b by examining the returns of Chinese lottery-type stocks. Due to the rather short time period (1994-2006), instead of using portfolio sorts, we use firm-level pooled cross-sectional regressions to examine the return seasonality of lottery-type stocks. Panel B of Table 9 reports the results. The dependent variable is the monthly individual stock returns minus the equal-weighted monthly market portfolio return. The independent variables include LOGPRC, IVOL, and the interactions of the two with a Chinese New Year month dummy, and a January dummy. The interaction term, LOG(PRC)×CNY, is equal to LOGPRC if the return is observed in the Chinese New Year month and zero otherwise. Similar definition applies to IVOL×CNY, LOGPRC×JAN, and IVOL×JAN. We run three specifications. In one, we include three variables associated with PRC. In the second, we include three variables associated with IVOL. In the third, we include all six. The *t*-statistics are based on standard errors that cluster over both time and firm dimensions.

As shown in Panel B of Table 9, we find strong evidence that lottery-type Chinese stocks outrperform in the Chinese New Year month, but not in January. The coefficient on the interaction term LOG(PRC)×CNY is always negative (−1.283 and −1.344) and significant at the 1% level. The coefficient on IVOL×CNY is always positive (0.988 and 1.039) and significant at the 10% and

[24]The two major Chinese exchanges, Shanghai and Shenzhen, were established at the end of 1990. DataStream starts to report their trading data from the beginning of 1992. Our analyses start from 1994 to ensure a sufficiently large cross section of stocks. From 1992 through 1993, there are a limited number of stocks reported in DataStream (less than 30 by the end of 1992 and less than 100 by the end of 1993). The results are stronger if we include data from 1993.

[25]In unreported tests, we find that the Shanghai and Shenzhen stock indexes, two major stock indexes in China, exhibit a weak January effect but a strong Chinese New Year effect. These indexes are value-weighted and based on large firms, and thus show a slightly different pattern from the equal-weighted market portfolio here.

the 5% level. In contrast, none of the interaction terms with the January dummy are significant explanatory variables. Taken together, our results are consistent with the hypothesis that Chinese investors exhibit a preference for lottery-type stocks at the start of the New Year, and not necessarily January unless the two periods coincide.

5. Conclusion

Gambling is a built-in preference of some individuals and tends to be stronger in the New Year. This paper provides a set of new evidence showing that such preference is exhibited in the financial markets and has a strong price impact on assets with lottery features in the New Year. The assets examined include OTM call options and lottery-type stocks in the US and China (where the New Year is not January 1$^{\mathbf{st}}$). We show that all of these assets have abnormally high prices, returns, and trading volume at the turn of the New Year. This seasonality contributes to, but differs from, previously known January effects, and carries important implications for trading strategies. Traditional hypotheses for the turn-of-the-year effect that involve tax-loss selling, window-dressing, or risk-shifting do not explain all of the effect.

Our empirical findings reveal novel seasonality in option implied volatility, volume, and behaviors of customers versus firms. We also find that the underperformance of high idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang 2006) and idiosyncratic skewness (Boyer, Mitton, and Vorkink 2008) stocks are pure non-January phenomena. Furthermore, the New Year effect of Chinese stocks poses an interesting puzzle for tax-loss-selling and institutional-trading based hypotheses.

Ritter (1988) suggests that the January effect is driven by investors' excess demand for small stocks after they "park" their selling proceeds for a while before re-investing them in January. The motive for parking the proceeds in December and buying small stocks in the New Year, however, was unspecified. Our evidence suggests that investors may have incentive to save cash to purchase lottery-type stocks in the New Year. As it is well said, "On ordinary days, you want to be disciplined. You don't want to waste your money. But on New Year's Day, it's your day off...You can do a little bit of the things that you would normally not want to do...You can say goodbye to your moral sense for the holiday."[26]

[26]Source: "Las Vegas bets big on Lunar New Year," by Spud Hilton, *San Francisco Chronicle*, February 10, 2008.

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Table 1: Media Citation on Gambling Mentality in the New Year

This table presents a small sampling of direct quotes from media articles in recent years. It shows that individuals in the US and worldwide actively engage in various types of gambling activities at the turn of the Yew Year.

Country	Date	Source	Title	Gaming Category	Quotes
USA	January 1, 2008	*Lotterypost.com*	"New Year's Eve lottery raffles from around the USA"	Raffles	*"In addition to celebrating the new year last night, lottery players from around the United States were checking their raffle tickets to see if they would start 2008 as a new millionaire."* *"Raffle games have become popular in recent years in the United States, and typically are held around the December holiday period."*
USA	April 12, 2000	*The Wall Street Journal*	"Casino firms face tough comparisons in period"	Casinos	*"The high rollers also poured into Mirage Resorts Inc.'s upscale Bellagio casino resort in Las Vegas, which did well for the 10 days in February marking the Chinese New Year celebration."*
USA	November 21, 2006	*Casinocitytimes.com*	"Gambling portal webmasters endure the UIGEA"	Internet	*"…The winter months are traditionally the busiest time of the year for online gaming companies."*
USA	December 28, 2008	*Shreveport Times*	"Local hotels staying busy"	Casinos	*"The week between Christmas and New Year's is typically weak for the hotel industry….If we didn't have the casinos…we wouldn't have any business this time of year."*
China/USA	February 10, 2008	*San Francisco Chronicle*	"Las Vegas bets big on Lunar New Year"	Casinos	*"MGM Mirage chairman Terry Lanni has called the Lunar New Year weekend bigger for wagering than the Super Bowl."* *"Chinese people at New Year's time always gamble. We always try to test our luck."*

Table 1: Media Citation on Gambling Mentality in the New Year: Cont'd

Country	Date	Source	Article Title	Gaming Category	Quotes
China/USA	January 29, 1998	*New York Times*	"Bettors Try to Ride the Tiger; Chinese Hope Good Luck Accompanies the New Year"	Casinos	*"While many people gathered in Chinatown today to watch the lion dance and New Year's parade, hundreds of others chose the baccarat tables, pai gow poker games and slot machines at the lavish casinos." "While buses run every day of the week to Foxwoods and Atlantic city, the weeklong celebration of Chinese New Year is among the casino's busiest times."*
Greece	December 30, 2005	*Bloomberg.com*	"Greece's New Year Gambling Tradition Bolsters Casinos' Earnings"	Casinos, Internet, Sportsbooks	*"…most of Greece's 11 million people will welcome the New Year in their traditional way: gambling." "During the holidays, families and companies gather to cut a cake and the person who finds a coin in his or her slice is said to enjoy good luck for the new year."*
New Zealand	December 21, 2004	*New Zealand Dept. of Internal Affairs*	"Gambling Inspectors, Christmas at casinos"	Casinos	*"The Department of Internal Affairs has Gambling Inspectors working in all six of the country's casinos. For them, Christmas is the busiest time of the year. There are far more gamblers in casinos at this time of year and much more is gambled." "With many more people in casinos, and many of them having indulged in the Christmas spirit, Inspectors are often called on to handle gamblers' complaints."*
Turkey	December 14, 2008	*Sundayszaman.com*	"Turks dream of big money as New Year's Eve approaches"	Lotteries	*"The hype surrounding the Dec. 31st jackpot is a normalized part of Turkish culture surrounding New Year's." "People if every age and background are buying tickets for the big drawing. Religious or not, young or old, male or female, the New Year's Jackpot has become an established part of the seasonal culture for a few weeks each year, as Turks set their worries aside and dream of what they would do with millions."*

Table 2: Summary statistics for US option, US stock, and China stock samples

In the first two rows of Panel A are statistics for the US option sample from 1996–2006 collected from OptionMetrics. The average annualized implied volatility (ImpVol), monthly volume (Volume), and adjusted option volume (Adj. Volume) across all firm-months are reported. OTM calls have a ratio of the strike price to stock price above 1.05 and ATM calls have a ratio between 0.975 and 1.025. We only include options with non-zero trading volume and contracts expiring in the following month. For a given stock, at the end of each month we compute the implied volatility as the average annualized implied volatility (in percent) of all OTM and ATM calls. For a given stock, the monthly volume of OTM (ATM) calls is calculated as the average monthly trading volume across all OTM (ATM) calls in a given month. To account for the upward time trend in option volume, for a given stock we separately compute for OTM and ATM calls the percentage change of the current month volume from its past 12-month moving average, and label it the adjusted option volume. The last five rows of Panel A show equity-based option volume data from OCC reports, including all strikes and maturities from 2000–2008. The average weekly option volume (Volume), call volume (Call), put volume (Put), and C/P ratios (C/P) across all account types are reported. For a given stock, weekly volume refers to the average weekly option volume, call volume refers to the average weekly volume on open buy call options, and put volume refers to the average weekly volume on open buy put options, all in thousands of contracts. The C/P ratio is the ratio of open buy call option volume divided by open buy put option volume. Open buys are new purchases of call options and include no buying to cover previous short call positions. "Firm" refers to an account established by a clearing member for the purposes of the clearing member. "Customer" refers to an account established by a clearing member on behalf of its customers. Based on the size of each transaction, customers are classified into three groups: 1–10 contracts per transaction, 11–49, and 50 and above. Panel B reports summary statistics of the US stock sample over the period 7/63–12/07. The lottery feature measures include stock price (PRC) (or logarithmic stock price, LOGPRC), idiosyncratic volatility (IVOL), idiosyncratic skewness (ISKEW), expected idiosyncratic skewness (EISKEW), and the lottery feature index (LOTT). PRC is the closing stock price measured at the end of the preceding month. IVOL is the standard deviation of at least 17 daily residual returns from the Fama-French three-factor model within the preceding month. ISKEW is the skewness of at least 26 weekly residual returns over the past 12 months, where the residual returns are obtained from the model with the market and squared market factors. EISKEW is the expected 12-month ahead weekly idiosyncratic skewness based on monthly forecasts. LOTT is the average ranking of PRC, IVOL, and EISKEW. For each feature the ranking is based on 20 portfolios sorted by the feature. These portfolios are indexed from 0 to 19, with 19 indicating the lowest PRC, highest IVOL, or highest EISKEW group. Panel C reports the summary statistics of the China stock sample from 1994–2006 for the monthly return (RET), logarithmic stock price (LOGPRC), and idiosyncratic volatility (IVOL). RET refers to percentage monthly returns, with months redefined to account for the Chinese New Year. LOGPRC is logarithmic stock price in local currency measured at the end of the preceding month. IVOL is the standard deviation of at least 15 daily residual returns in the preceding month from the regression of daily returns on both the Shanghai and Shenzhen A share indices.

Table 2: Summary statistics for US option, US stock, and China stock samples: Cont'd

Panel A: US option sample				
OptionMetrics	Ave. # of firms	ImpVOL	Volume	Adj. Volume
ATM Calls	1963	42.33	1852	0.119
OTM Calls	1963	55.32	775	0.077
OCC Reports	Volume	Call	Put	C/P
Firm	3684	1885	1799	1.30
Customer	11542	6617	4925	1.64
1-10	2149	1404	745	2.23
11-49	2320	1448	873	2.05
50 and up	7073	3765	3307	1.36

Panel B: US stock sample				
	# of firm-month obs	Mean	Median	Stdev
LOGPRC	2,545,129	2.27	2.50	1.25
IVOL	2,513,228	2.96	2.23	2.75
ISKEW	2,471,403	0.62	0.52	1.02
EISKEW	1,868,909	0.60	0.58	0.38
LOTT	2,558,395	9.66	10.00	4.78

Panel C: China stock sample				
	# of firm-month obs	Mean	Median	Stdev
RET	72,376	0.21	−1.06	14.70
LOGPRC	72,376	2.01	2.03	0.54
IVOL	72,376	1.61	1.42	0.87

Table 3: Summary statistics of lottery feature portfolios, correlation matrix, and regressions to forecast idiosyncratic skewness

Panel A reports the characteristics of quintiles sorted on the lottery feature index (LOTT) over the period 7/63–12/07. LOGPRC is the logarithmic stock price. IVOL is the idiosyncratic volatility, EISKEW is the expected idiosyncratic skewness. ISKEW is the idiosyncratic skewness. All are defined in Table 2. ME(%) refers to the total market capitalization within the quintile as a percentage of the total market cap across all firms. Panel B reports the correlations between lottery feature measures and other firm characteristics. RET(-1) and RET(-12, -2) refer to the return in the prior month and the prior 2[nd] through 12[th] months, respectively. LOGME is logarithmic firm size, defined as the market equity measured at the end of the preceding month. LOGBM is logarithmic book-to-market equity. Book-to-market equity (BM), from June of year s through May of year $s+1$, is book equity measured at the fiscal year-end through December of year $s-1$, over market equity measured at the end of December of year $s-1$. Share turnover (TURN) is the total monthly trading volume over shares outstanding in the preceding month, multiplied by 100. Trading volume of NASDAQ firms is divided by two. Panel C reports the average coefficients of the monthly cross-sectional regressions of future ISKEW measured over months t through $t+11$ on past ISKEW measured over months $t-12$ through $t-1$, and a set of firm characteristics. EISKEW in month t is calculated based on ISKEW and other firm characteristics observed at the end of month $t-1$ and the regression coefficients estimated in month $t-12$. The time series means of the coefficients from monthly cross-sectional regressions are reported with the Newey-West (1987) t-statistics in brackets.

Panel A: Summary statistics of portfolios sorted based on LOTT

LOTT rank	Ave. # firms	LOTT	LOGPRC	IVOL	EISKEW	ISKEW	ME (%)
L	958	2.85	3.57	1.26	0.25	0.28	81.86%
2	964	6.70	2.87	1.79	0.47	0.50	10.75%
3	959	9.80	2.46	2.22	0.63	0.63	4.25%
4	954	12.83	1.83	3.11	0.80	0.77	2.01%
H	949	16.13	1.07	5.58	1.05	1.00	1.14%

Panel B: Correlation matrix

	IVOL	ISKEW	EISKEW	LOTT	LOGME	LOGBM	RET(-1)	RET($-12, -2$)	TURN
LOGPRC	-0.54	-0.19	-0.80	-0.75	0.73	-0.09	0.09	0.24	0.08
IVOL		0.15	0.51	0.58	-0.34	-0.06	0.15	-0.12	0.12
ISKEW			0.37	0.25	-0.24	0.09	0.11	0.18	-0.01
EISKEW				0.82	-0.83	0.18	-0.07	-0.27	-0.19
LOTT					-0.73	0.05	-0.01	-0.16	-0.04

Panel C: Firm-level monthly cross-sectional regression to forecast EISKEW

	Intercept	LOGPRC	IVOL (*100)	ISKEW	LOGME	LOGBM (*100)	RET(-1) (*100)	RET($-12, -2$) (*100)	TURN (*100)
Coeffient	1.22	-0.11	1.03	0.05	-0.08	1.60	-0.10	-0.09	-0.30
t-statistic	[61.42]	[16.48]	[6.31]	[26.97]	[26.98]	[5.94]	[7.90]	[14.09]	[6.25]

Table 4: Implied volatility and adjusted option volume of call options

Panel A reports the mean monthly implied volatility spreads, first averaged across all firms and then averaged across years for a given month. It shows that the implied volatility spread between out-of-the-money (OTM) and at-the-money (ATM) calls is higher in January than in other months. That is, relative to ATM calls, OTM calls are the most expensive in January. Panel B reports the average monthly adjusted volume spread, first averaged across all firms and then average across years for a given month. It shows that the adjusted option trading volume spread between OTM and ATM calls is higher in January than in other months. That is, relative to ATM calls, OTM calls are most heavily traded in January. OTM and ATM calls are defined in Table 2. In brackets are bootstrapped t-statistics.

Panel A: Implied volatility

	Jan	**Non-Jan**	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
OTM	**57.36**	**54.40**	55.70	55.53	57.00	54.46	53.04	52.59	51.92	53.40	55.57	54.23	54.98
ATM	**43.88**	**45.01**	44.86	48.09	46.96	44.11	43.95	42.80	43.58	44.27	45.87	46.41	44.23
OTM−ATM	**0.13**	**0.09**	0.11	0.07	0.10	0.10	0.09	0.10	0.08	0.09	0.10	0.08	0.11
t(OTM−ATM)	**[8.00]**	**[13.61]**	[6.02]	[5.26]	[3.53]	[11.81]	[14.45]	[6.89]	[2.92]	[3.63]	[8.18]	[1.38]	[5.36]
Jan−(NonJan)		**0.04**											
t(Jan−(NonJan))		**[5.55]**											

Panel B: Option volume

	Jan	**Non-Jan**	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
OTM	**0.49**	**0.04**	−0.27	0.21	0.06	0.01	0.14	0.34	−0.08	−0.10	0.22	−0.08	−0.01
ATM	**0.27**	**0.10**	−0.19	0.19	0.40	0.05	0.09	0.23	−0.12	0.27	0.19	−0.21	0.25
OTM−ATM	**0.22**	**−0.06**	−0.08	0.02	−0.35	−0.03	0.05	0.11	0.04	−0.37	0.02	0.13	−0.26
t(OTM−ATM)	**[1.79]**	**[1.49]**	[0.59]	[0.12]	[2.16]	[0.24]	[0.41]	[0.69]	[0.31]	[4.68]	[0.13]	[1.25]	[2.73]
Jan−(NonJan)		**0.29**											
t[Jan−(NonJan)]		**[2.09]**											

Table 5: Open buy call/put volume and premium ratios of customers versus firms

Panel A reports the mean open buy call/put ratios by customer type and firm. The difference between January and non-January is reported under Jan−(NonJan). The difference between customer type and firm of open buy call/put ratios in January is reported for each customer type under $(\text{Customer}-\text{Firm})_{\text{Jan}}$. Panel B reports the average premium per option for the open call contracts purchased by customers, versus firms, within January and all other months. Based on the size of each transaction, customers are classified into three groups: 1–10 contracts per transaction, 11–49, and 50 and above. The average premium of the option is calculated as the dollar value of the total weekly premium divided by the number of contracts purchased. Panel C reports the average premium per option for the open put buy contracts. In all three panels, January weeks are defined as all weeks with a Friday ending in January. Non-January weeks include all other weeks. The difference between customer type and firm of open buy premium differentials, between January and other months, is reported for each customer type under $(\text{Customer}-\text{Firm})_{\text{Jan}-\text{NonJan}}$. In brackets are bootstrapped t-statistics.

Panel A: Open buy call/put ratio					
	Customer				Firm
	All	1−10	11−49	50&Up	All
Jan	1.613	2.429	2.060	1.342	1.293
NonJan	1.451	2.122	1.838	1.226	1.165
Jan−(NonJan)	0.162	0.307	0.222	0.116	0.128
t[Jan−(NonJan)]	[1.89]	[2.04]	[2.19]	[1.90]	[2.39]
$(\text{Customer}-\text{Firm})_{\text{Jan}}$	**0.320**	**1.140**	**0.770**	**0.050**	
$t[(\text{Customer}-\text{Firm})_{\text{Jan}}]$	**[2.21]**	**[5.50]**	**[4.62]**	**[0.49]**	

Panel B: Open buy call premium					
	Customer				Firm
	All	1−10	11−49	50&Up	All
Jan	3.662	3.696	2.693	2.693	4.328
NonJan	3.182	3.297	2.379	2.237	3.203
Jan−(NonJan)	0.480	0.399	0.313	0.456	1.126
t[Jan−(NonJan)]	[1.39]	[3.88]	[5.96]	[6.74]	[8.35]
$(\text{Customer}-\text{Firm})_{\text{Jan}-\text{NonJan}}$	**−0.736**	**−0.727**	**−0.812**	**−0.670**	
$t[(\text{Customer}-\text{Firm})_{\text{Jan}-\text{NonJan}}]$	**[2.28]**	**[2.25]**	**[2.59]**	**[2.00]**	

Panel C: Open buy put premium					
	Customer				Firm
	All	1−10	11−49	50&Up	All
Jan	3.217	3.151	2.591	2.687	6.306
NonJan	2.738	2.927	2.400	2.483	6.074
Jan−(NonJan)	0.479	0.225	0.191	0.204	0.232
t[Jan−(Non-Jan)]	1.55	5.99	7.39	3.18	0.18
$(\text{Customer}-\text{Firm})_{\text{Jan}-\text{NonJan}}$	**−0.026**	**−0.007**	**−0.041**	**−0.028**	
$t[(\text{Customer}-\text{Firm})_{\text{Jan}-\text{NonJan}}]$	**[0.03]**	**[0.01]**	**[0.04]**	**[0.03]**	

Table 6: Monthly returns of portfolios sorted on lottery features

This table shows that stocks with strong lottery features outperform those with weak lottery features in January, but tend to underperform in other months, for both value-weighted (Panel A) and equal-weighted (Panel B) returns. It reports the average monthly percentage returns of quintiles of stocks sorted on stock price (PRC), idiosyncratic volatility (IVOL), expected idiosyncratic skewness (EISKEW), and the lottery feature index (LOTT). The variables PRC, IVOL, EISKEW, and LOTT are defined in Table 2. Average percentage returns of these quintiles, from 7/63–12/07, are shown across all months, in January and in non-January months. W(weak) refers to the lowest LOTT, IVOL, or EISKEW, and the highest PRC quintile. S(strong) refers to the highest LOTT, IVOL, or EISKEW quintile, and the lowest PRC quintile. S−W refers to the long minus short portfolio that is long the strongest lottery feature quintile and short the weakest quintile. α(S−W) for all months, January, and non-January months refers to the monthly average abnormal return across those periods, where the abnormal return is defined relative to the three-factor model with factor loadings estimated using all months over the full sample. Newey-West (1987) t-statistics are reported in brackets.

	All months				January				Non-January			
Panel A: Value-weighted												
Rank	LOTT	PRC	IVOL	EISKEW	LOTT	PRC	IVOL	EISKEW	LOTT	PRC	IVOL	EISKEW
W (Weak)	0.96	0.94	0.96	0.89	1.61	1.51	1.53	1.46	0.90	0.89	0.91	0.83
2	1.03	1.03	1.03	1.07	3.52	2.97	2.19	2.91	0.80	0.86	0.92	0.90
3	0.82	1.00	1.07	1.05	3.67	4.54	3.08	4.62	0.56	0.69	0.89	0.73
4	0.59	0.83	0.73	0.92	5.88	7.55	3.65	7.63	0.12	0.22	0.47	0.31
S(Strong)	0.38	0.90	−0.01	1.04	8.82	12.56	5.43	12.36	−0.38	−0.15	−0.50	0.01
S−W	−0.58	−0.04	−0.97	0.15	7.21	11.05	3.91	10.90	−1.28	−1.04	−1.41	−0.83
	[1.74]	[0.11]	[3.02]	[0.44]	[4.04]	[5.47]	[3.41]	[5.44]	[3.80]	[3.07]	[4.19]	[2.45]
α(S−W)	−0.86	−0.63	−1.26	−0.46	4.13	6.53	0.92	5.94	−1.31	−1.28	−1.46	−1.05
	[4.09]	[2.69]	[6.38]	[2.32]	[2.60]	[4.02]	[1.59]	[3.92]	[5.87]	[5.27]	[6.99]	[4.94]
Panel B: Equal-weighted												
Rank	LOTT	PRC	IVOL	EISKEW	LOTT	PRC	IVOL	EISKEW	LOTT	PRC	IVOL	EISKEW
W (Weak)	1.20	1.14	1.17	1.04	2.24	1.90	2.83	1.72	1.11	1.08	1.02	0.98
2	1.33	1.20	1.39	1.17	3.99	3.36	4.15	3.04	1.09	1.01	1.14	1.00
3	1.24	1.16	1.40	1.20	5.16	5.04	5.60	4.96	0.89	0.81	1.02	0.86
4	1.19	0.94	1.25	1.07	8.03	7.75	7.71	7.83	0.58	0.32	0.67	0.45
S(Strong)	1.42	1.94	1.10	1.92	13.72	15.05	12.85	14.80	0.32	0.76	0.04	0.75
S−W	0.22	0.79	−0.07	0.88	11.48	13.15	10.01	13.08	−0.80	−0.32	−0.98	−0.23
	[0.69]	[2.50]	[0.23]	[2.81]	[5.51]	[6.40]	[5.63]	[6.10]	[2.64]	[1.12]	[3.03]	[0.82]
α(S−W)	−0.08	0.36	−0.39	0.37	8.51	9.76	7.05	8.98	−0.86	−0.49	−1.07	−0.43
	[0.37]	[1.53]	[1.87]	[1.72]	[4.35]	[5.05]	[4.60]	[4.70]	[4.04]	[2.13]	[5.05]	[1.99]

Table 7: Month-by-month long-short portfolio returns

This table shows that the significant overperformance of lottery-type stocks occurs mainly in January. Panels A and B report the month-by-month average value- and equal-weighted long-short portfolio returns, respectively. The long-short portfolio is long the strongest lottery feature quintile and short the weakest feature quintile. The lottery features include low stock price (PRC), high idiosyncratic volatility (IVOL), high expected idiosyncratic skewness (EISKEW), and high lottery-feature index (LOTT), all defined in Table 2. Newey-West (1987) t-statistics are reported in brackets.

Panel A: Value-weighted

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
PRC	11.05	0.78	0.25	−1.47	0.40	−1.89	−1.40	−1.21	−0.78	−2.55	−0.70	−2.75
	[5.47]	[0.80]	[0.34]	[2.69]	[0.39]	[3.07]	[1.86]	[1.68]	[0.92]	[2.15]	[0.44]	[2.31]
IVOL	3.91	−0.56	−1.72	−0.90	−1.17	−1.33	−2.59	−0.56	−1.54	−3.39	−0.21	−1.58
	[3.41]	[0.57]	[1.63]	[1.11]	[1.16]	[1.54]	[2.83]	[0.98]	[1.64]	[4.41]	[0.20]	[1.74]
EISKEW	10.90	1.77	−0.13	−1.05	0.19	−1.02	−0.96	−1.23	−0.41	−3.45	−1.03	−1.90
	[5.44]	[2.01]	[0.19]	[1.86]	[0.19]	[1.63]	[1.20]	[1.72]	[0.52]	[4.85]	[0.84]	[1.60]
LOTT	7.21	0.16	−1.32	−1.73	−0.24	−2.11	−2.14	−1.28	−0.83	−1.95	−0.77	−1.88
	[4.04]	[0.19]	[1.71]	[2.44]	[0.27]	[3.63]	[3.07]	[1.97]	[1.18]	[1.85]	[0.53]	[1.87]

Panel B: Equal-weighted

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
PRC	13.15	2.12	1.06	0.13	0.89	−1.06	0.04	−0.81	−0.06	−1.36	−1.46	−2.86
	[6.40]	[2.55]	[1.74]	[0.31]	[1.08]	[1.82]	[0.09]	[1.45]	[0.11]	[1.83]	[1.32]	[2.42]
IVOL	10.01	0.67	−0.50	−0.80	−0.47	−1.30	−1.69	−0.95	−0.78	−1.98	−0.61	−2.41
	[5.63]	[0.67]	[0.78]	[1.28]	[0.63]	[2.43]	[3.08]	[2.01]	[0.98]	[2.85]	[0.54]	[2.71]
EISKEW	13.08	2.56	0.81	−0.09	0.69	−0.29	0.32	−0.84	0.17	−2.13	−1.46	−2.40
	[6.10]	[3.06]	[1.49]	[0.16]	[0.85]	[0.51]	[0.62]	[1.40]	[0.29]	[3.41]	[1.55]	[2.08]
LOTT	11.48	1.30	−0.26	−0.49	0.07	−1.44	−0.81	−1.17	−0.35	−1.55	−1.24	−2.73
	[5.51]	[1.59]	[0.45]	[0.90]	[0.09]	[2.95]	[2.03]	[2.12]	[0.56]	[2.40]	[1.17]	[2.55]

Table 8: Fama-MacBeth regressions at the firm level for January returns

Panel A shows that the three lottery feature variables and the lottery index independently and incrementally, relative to a number of well-known return predictors and measures of systematic risk, forecast individual stock returns in January. It reports the firm-level Fama-MacBeth (1973) regression results during 1/64–1/07 for January returns. The dependent variable is the percentage January returns of individual stocks. LOTT, LOGPRC, IVOL, EISKEW, ME, BM, RET(−1), RET(−12, −2), and RET(−36, −13) are defined in Tables 2 and 3. LOGME is logarithmic market equity. LOGBM is logarithmic book-to-market equity. β_{MKT}, β_{SMB}, and β_{HML} refer to loadings on the three Fama-French factors, which are estimated using at least 15 daily returns within the current January from the Fama-French three-factor model. Panel B splits the full sample based on past returns or institutional trading in the first quarter of the year, and shows that the forecast power of LOTT is significant for all subsamples. The specifications (1)–(4) in Panel A are run in Panel B. WINNER refers to stocks with positive past twelve-month returns as of the most recent December. LOSER refers to those with negative cumulative returns over the same horizon. IO-NBUY refers to stocks that are either untraded or net sold by institutions, defined as no net change or a net decrease in institutional ownership, in the first quarter of the current year. IO-BUY refers to stocks that are net bought by institutions, defined as a net increase in institutional ownership over the same time horizon. LOTT' is re-defined lottery feature index using only stocks in each of the subsamples. The control variables include all other characteristics and factor loadings in Panel A. All returns are expressed on a monthly basis. Newey-West (1987) t-statistics are reported in brackets. The R-squares are adjusted for degrees of freedom and their time series means are reported.

Panel A: Full sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
LOTT	0.812					0.312				
	[5.92]					[3.54]				
LOGPRC		−4.441					−3.244			−1.774
		[6.95]					[5.63]			[2.84]
IVOL			1.462					0.752		0.300
			[7.84]					[6.71]		[2.39]
EISKEW				14.582					13.908	5.689
				[7.00]					[5.45]	[1.94]
LOGME					−1.554	−0.930	−0.164	−1.065	0.402	0.131
					[7.83]	[7.63]	[1.07]	[6.33]	[1.42]	[0.42]
LOGBM					0.028	0.184	0.243	0.264	0.194	0.410
					[0.09]	[0.63]	[0.88]	[0.93]	[0.83]	[1.19]
RET(−1)					−0.142	−0.144	−0.124	−0.161	−0.121	−0.140
					[7.00]	[7.08]	[6.89]	[7.79]	[5.45]	[4.95]
RET(−12, −2)					−0.202	−0.174	−0.094	−0.166	−0.046	−0.061
					[3.56]	[3.51]	[2.27]	[3.28]	[0.89]	[1.17]
RET(−36, −13)					−0.316	−0.283	−0.187	−0.265	−0.221	−0.182
					[4.03]	[4.12]	[3.49]	[3.88]	[3.82]	[3.57]
β_{MKT}					1.135	1.073	1.029	1.033	0.934	0.888
					[5.46]	[5.17]	[5.14]	[5.45]	[5.78]	[5.73]
β_{SMB}					0.283	0.260	0.265	0.269	0.288	0.293
					[2.03]	[2.03]	[2.11]	[2.16]	[2.28]	[2.39]
β_{HML}					0.005	−0.283	−0.014	0.007	−0.059	−0.079
					[0.03]	[4.12]	[0.07]	[0.04]	[0.31]	[0.43]
INTERCEPT	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
R^2	5%	8%	4%	9%	13%	13%	14%	14%	15%	16%

Table 8: Fama-MacBeth regressions at the firm level for January returns: Cont'd

Panel B: Subsamples based past returns and institutional trading				
	WINNER	LOSER	IO-NBUY	IO-BUY
(1)				
LOTT'	0.350	0.503	0.458	0.479
	[5.13]	[5.15]	[3.35]	[3.66]
(2)				
LOG(PRC)	−2.036	−3.700	−3.116	−3.505
	[5.81]	[5.57]	[3.57]	[3.82]
(3)				
IVOL	0.416	0.606	0.634	1.137
	[3.83]	[3.97]	[4.24]	[3.26]
(4)				
EISKEW	8.271	15.848	13.783	14.632
	[4.52]	[4.79]	[4.79]	[3.79]
Specifications (1)–(4)				
Controls	YES	YES	YES	YES
INTERCEPT	YES	YES	YES	YES

Table 9: Chinese stock returns: January versus the Chinese New Year

Panel A reports the average monthly percentage returns of the equal-weighted market portfolio over three time intervals for the period 1/94–12/06 for Chinese A shares. The time periods are the Chinese New Year Month (CNY), defined as a 22-trading-day window beginning the first trading-day of the Chinese New Year, trading days in January that precede the New Year Month (JAN), and other times of the year from March through December (OTHER). Other times includes all trading-days in April through December, and trading-days in February and March after the New Year Month. All such February returns are treated as if they occur in March. To account for the variable number of trading days in January and March, portfolio returns are divided by the number of valid trading days within the month and multiplied by 22. Thus, all returns are expressed on a monthly basis. Panel B reports the results of a pooled cross-sectional regression at the firm level. The dependent variable is the monthly individual stock returns minus the equal-weighted monthly market portfolio return. The two lottery feature variables are logarithmic stock price, LOGPRC, and idiosyncratic volatility, IVOL. PRC is defined as the closing price of the last trading day of the previous month. IVOL is the standard deviation of at least 15 daily residual returns in the preceding month from the regression of daily returns on both the Shanghai and Shenzhen A share indices. When the number of trading days in the preceding month is less than 15 for the overall market, IVOL from month $t-2$ is used. LOGPRC×CNY is equal to LOGPRC when the return is measured over the Chinese New Year Month, and zero otherwise. LOGPRC×JAN is equal to LOGPRC when the return is measured over January, and zero otherwise. Similar definitions hold for IVOL×CNY and IVOL×AN. T-statistics reported in brackets are based on standard errors that cluster over both firm and time.

Panel A: Equal-weighted market portfolio

ALL MONTHS	CNY	JAN	OTHER
1.18	5.92	−1.53	0.97
[0.94]	[2.64]	[0.36]	[0.68]

Panel B: Pooled cross-sectional regression

	(1)	(2)	(3)
LOGPRC	−0.889		−0.860
	[5.78]		[5.55]
LOGPRC×CNY	**−1.283**		**−1.344**
	[2.50]		**[2.57]**
LOGPRC×JAN	−0.466		−0.496
	[0.08]		[0.90]
IVOL		−0.479	−0.419
		[3.86]	[3.34]
IVOL×CNY		**0.988**	**1.039**
		[1.80]	**[2.05]**
IVOL×JAN		0.495	0.456
		[1.09]	[1.06]
INTERCEPT	YES	YES	YES
R^2	1.10%	0.19%	1.26%

Figure 1: January seasonality of the per capita gaming revenue from the Las Vegas Strip

This figure shows that casino gambling in Las Vegas exhibits January seasonality. Panel A depicts the year-by-year average monthly per capita gaming revenue from the Las Vegas Strip in January and non-January months over the period 1997–2007. The per capita gaming revenue is defined as the monthly gaming revenue over the total number of monthly visitors in Las Vegas. Panel B depicts the month-by-month per capital gaming revenue, averaged across the eleven-year period, and the percentage of monthly visitors relative to annual visitors and to total monthly population. The per capita gaming revenues in Panel B are defined as monthly gaming revenues over either total monthly population (including local residents and visitors) or the total number of monthly visitors.

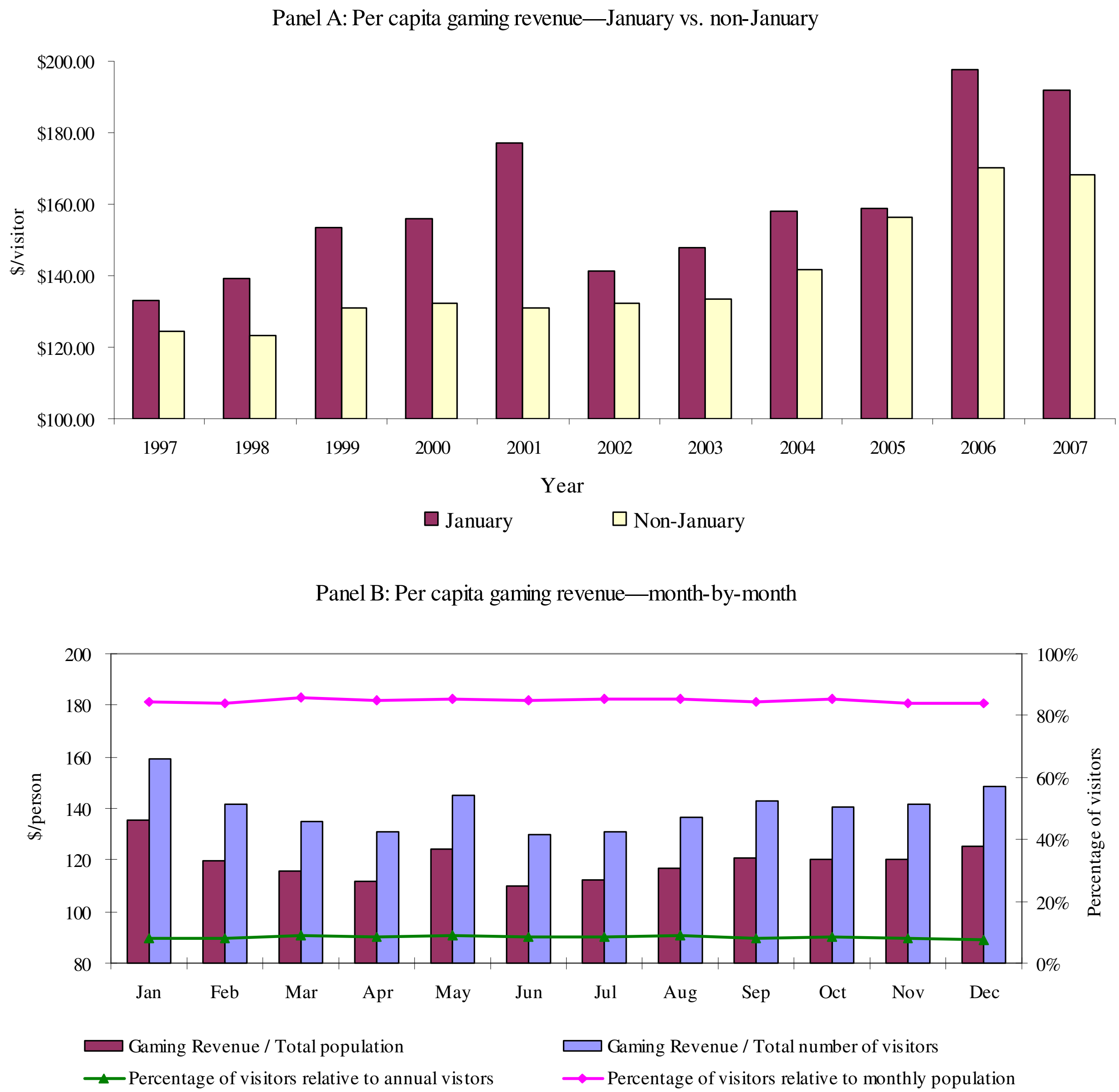


Figure 2: January returns on the hedge portfolios based on the lottery feature index

Panels A and B depict the year-by-year January raw returns on the hedge portfolio that is long the highest lottery index (LOTT) quintile and short the lowest quintile. In Panel B, stocks with the end-of-December price below \$5 are excluded. Panels C and D depict the ROLL-adjusted January returns for the two portfolios. The returns are equal-weighted. For each firm we compute the bid-ask-spread-adjusted returns as the raw percentage returns minus the percentage effective bid-ask spread (ROLL) proposed by Roll (1984). These figures show that the trading strategy based on lottery features involves limited downside risk over the sample period.

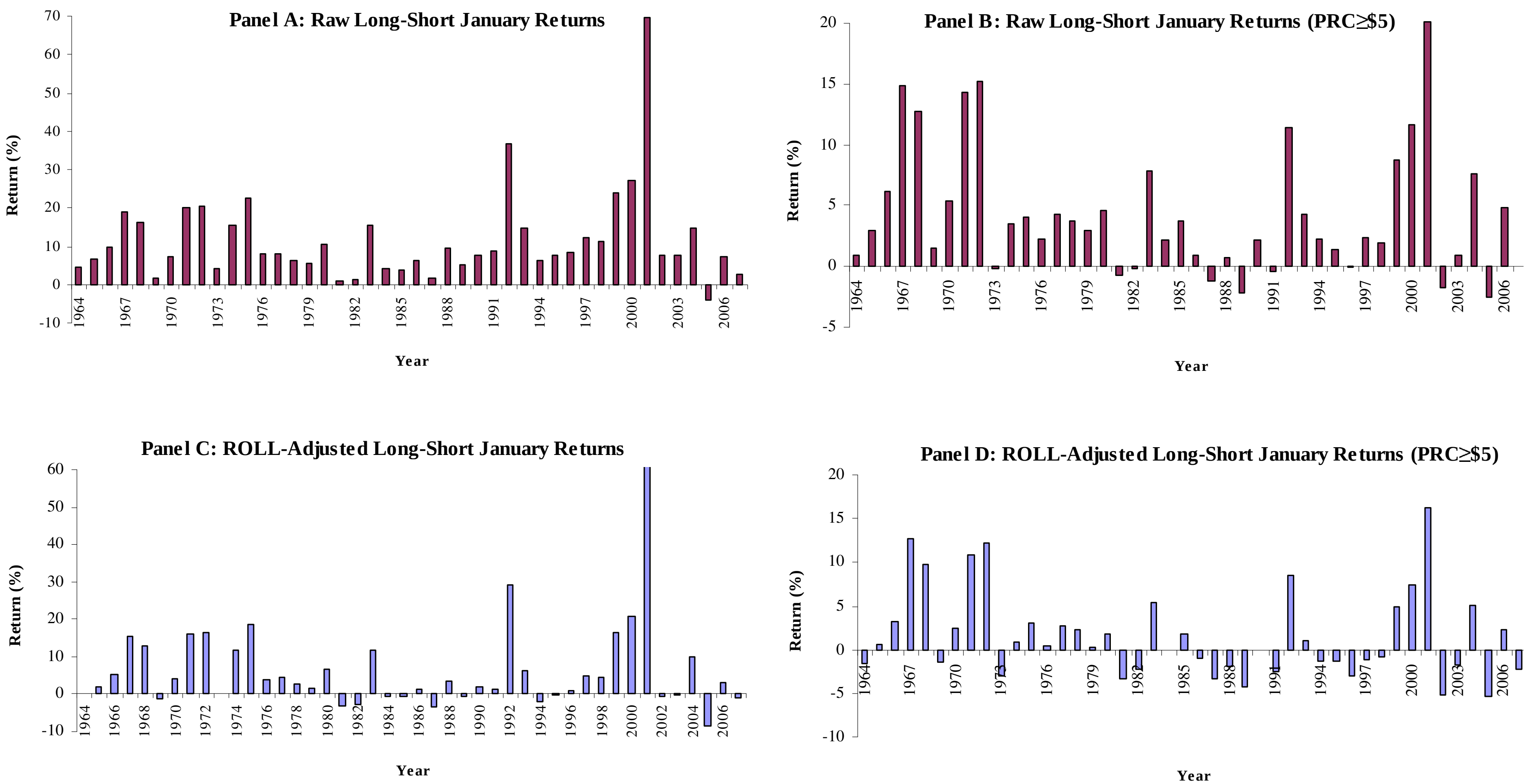
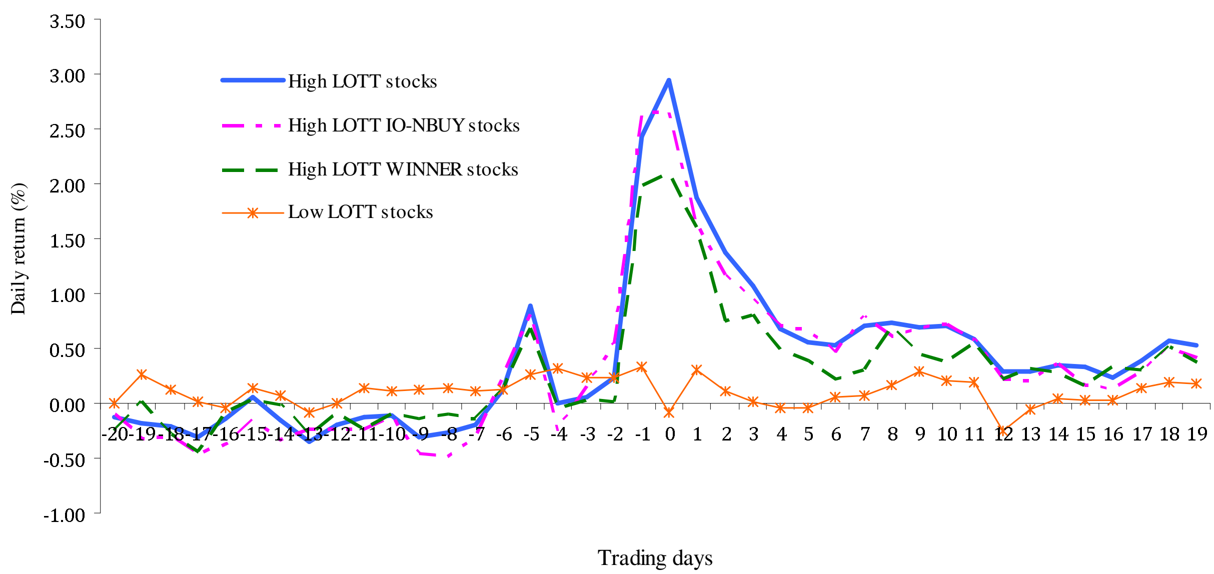


Figure 3: Daily returns and excess turnover of lottery-type stocks at the turn-of-the-year

The figure depicts average daily returns and excess turnover for 20 trading-days before through 20 trading-days after January 1st over the period 1964–2007. Day 0 is the first trading-day in January. Stocks must have positive daily turnover to be included. High LOTT stocks are defined as the top quintile of stocks based on the lottery-feature index (LOTT), defined in Table 1. High LOTT WINNER stocks are lottery-type stocks, defined as above, with positive past 12-month returns as of the end of November of the previous year. High LOTT IO-NBUY stocks are lottery-type stocks (defined as above) without a net increase in institutional ownership during the first quarter of the current year. Low LOTT stocks are defined as the bottom quintile based on LOTT. Excess turnover is defined as the percentage change in the daily turnover from its average over February through November of the previous year. The portfolio composition remains constant across the trading days. Daily returns and excess turnover are equal-weighted and in percent.

Panel A: Average daily returns at the turn-of-the-year



Panel B: Average daily excess turnover at the turn-of-the-year

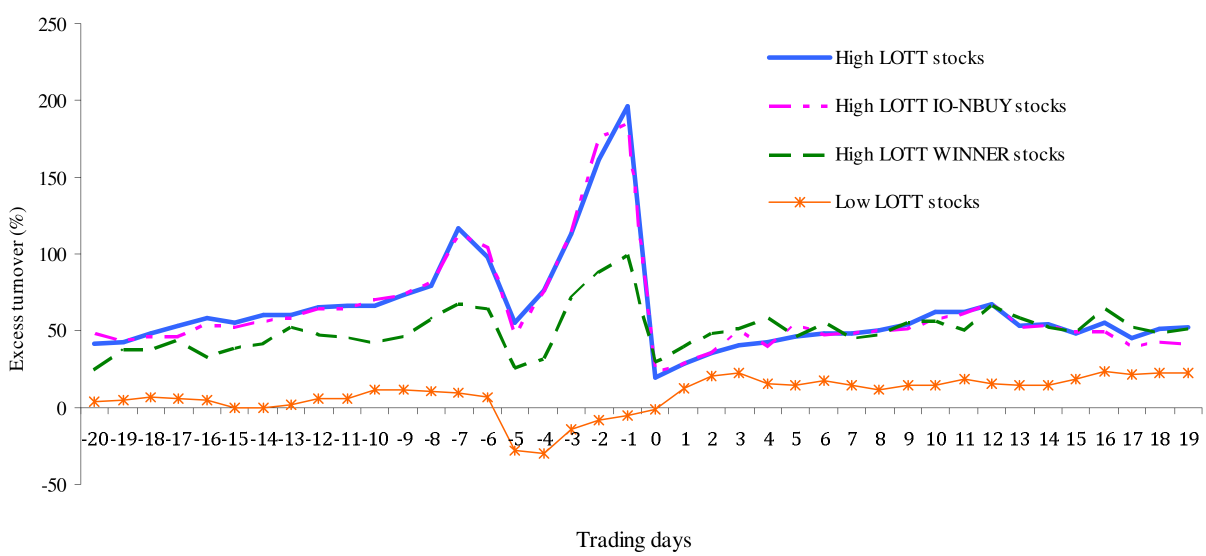
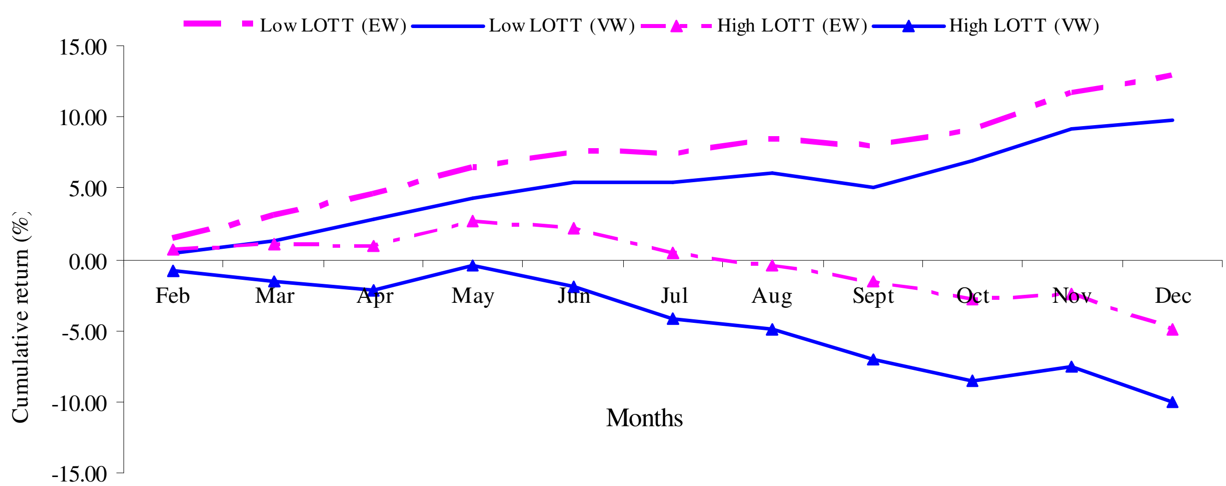


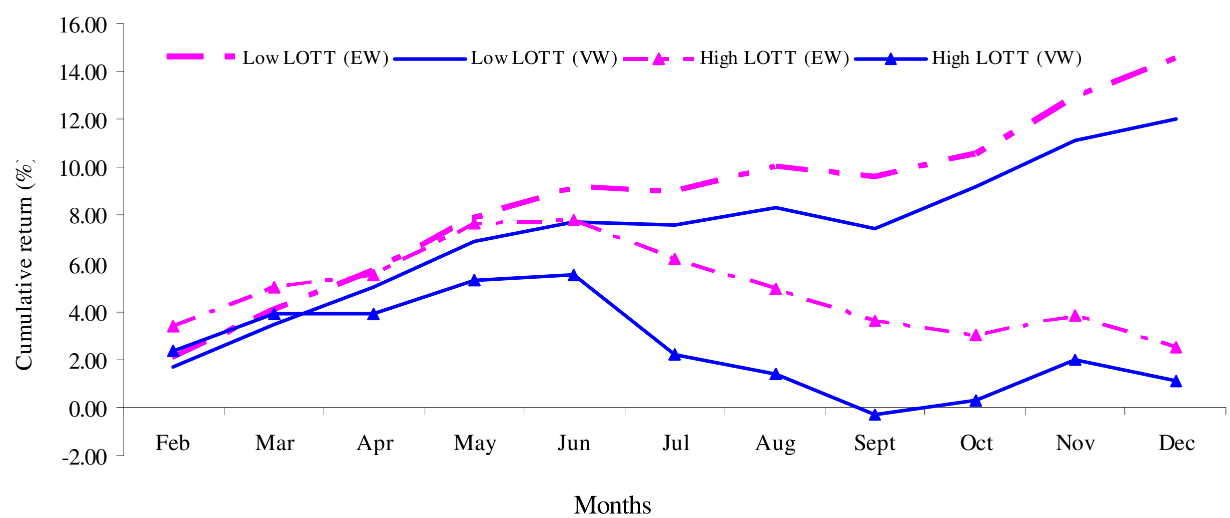
Figure 4: Cumulative buy-and-hold returns from February to December based on the lottery index and changes in institutional ownership

The figure in Panel A depicts the cumulative percentage value- and equal-weighted returns on the highest (H) and the lowest (L) lottery index (LOTT) quintiles of stocks for which institutional investors are net sellers in the first quarter of the year from 1981 through 2007. Panel B depicts these returns for stocks for which institutional investors are net buyers in the first quarter of the year. The LOTT quintiles are formed at the end of the December preceding January of year s. We keep the composition of each quintile constant and compute value- and equal-weighted quintile monthly returns from February to December of year s. Then we cumulate these mean quintile monthly returns separately for each month from February through December. Delisting returns are incorporated in the month of delisting. If delisting returns are missing they are replaced by -30% (Shumway 1997). The figures show that for the year excluding January, stocks in the highest LOTT quintile are expected to have lower returns than those in the lowest LOTT quintile. In particular, among stocks for which individual investors are net buyers the lottery-type stocks are expected to deliver negative returns by the end of the year.

Panel A: Stocks with institutions as the net sellers



Panel B: Stocks with institutions as the net buyers



Appendix

The appendix presents supplementary results about the robustness of our findings.

A. Alternative Measures

This section shows that our main results are robust to alternative measures of idiosyncratic volatility (IVOL) or idiosyncratic skewness (ISKEW).

1 Idiosyncratic volatility

We consider five alternative measures of idiosyncratic volatility (IVOL). For each measure of IVOL, we sort stocks based on their December measure into quintiles and compute the mean quintile returns in the following January. The evidence presented in Table A1 shows that the highest IVOL quintile on average outperforms the lowest IVOL quintile in January for all measures.

[INSERT TABLE A1 HERE]

1.1 IVOL based on past 3-month daily returns

We compute the daily residual returns from the Fama-French 3-factor models using at least 30 out of the 62 daily returns over the past 3 months. IVOL_{D} is defined as the standard deviation of the residual returns.

1.2 IVOL based on past 12-month weekly returns

We compute the weekly residual returns from the Fama-French 3-factor models using at least 30 out of the 52 weekly returns over the past 12 months. IVOL_{W} is defined as the standard deviation of the residual returns.

1.3 IVOL based on the EGARCH model

Following Fu (2008) and Spiegel and Wang (2006), we apply the EGARCH model (Nelson 1991) to compute the expected idiosyncratic volatility. The function form for the EGARCH is,

$$r_{j,t} = \alpha_j + \beta_{m,j}\text{MKT}_\text{t} + \beta_{s,j}\text{SMB}_\text{t} + \beta_{h,j}\text{HML}_\text{t} + \epsilon_{j,t}, \qquad \epsilon_{j,t} \approx N(0, \sigma^2_{j,t}) \tag{A-1}$$

$$\ln \sigma^2_{\text{EG}_{\text{IVOL}},j,t} = \alpha_j + \sum_{\phi=1}^{p} b_{j,\phi} \ln \sigma^2_{j,t-1} + \sum_{\psi=1}^{q} c_{j,\psi}\{\theta \frac{\epsilon_{j,t-k}}{\sigma_j, t-l} + \gamma \left[\left| \frac{\epsilon_{j,t-k}}{\sigma_j, t-l} \right| \right] - \sqrt{\frac{2}{n}}\} \tag{A-2}$$

where monthly residual returns are computed from the three-factor model in equation (A-1), and the conditional variance for firm j, $\sigma^2_{\text{EG}_{\text{IVOL}},j,t}$, is computed from the past p residual variances and q-period return shocks. Equations (A-1) and (A-2) are estimated for each stock using at least the past 60 monthly returns from month $t-60$ through $t-1$. $\text{IVOL}_{\text{EGARCH}}$ is defined as the square root of $\sigma^2_{\mathrm{EG_{IVOL}},j,t}$. The benefit of the EGARCH versus the GARCH model is that is does not require restricting the parameters to insure a non-negative variance.

1.4 IVOL based on the AR(2) model

Following Chua, Goh, and Zhang (2007), in the AR(2) model, we use the squared residual from equation (A-1). The idiosyncratic variance for firm j is defined as:

$$\sigma^2_{\mathrm{AR_{IVOL}},j,t} = \theta_{1,j} + \theta_{2,j}\varepsilon^2_{j,t-1} + \theta_{3,j}\varepsilon^2_{j,t-2} + \eta_{j,t}. \tag{A-3}$$

An AR(2) is preferred to an AR(1) process since the latter tends to have high serial correlation. $\mathrm{IVOL_{AR(2)}}$ is defined as the square root of $\sigma^2_{\mathrm{AR_{IVOL}},j,t}$.

1.5 IVOL based on option implied volatility

Following Diavatopoulos, Doran, and Peterson (2008), we use daily implied volatility data, obtained from Optionmetrics, from January 1996 through June 2006 to compute implied volatility. Since there are a variety of strike prices and maturities for each firm on a given day, we calculate a standardized implied volatility by employing the most weight on implied volatilities with at-the-money options closest to 30 days to expiration for both calls and puts. The implied volatility for a stock is defined as the average implied volatility across all options to reduce the measurement error associated with inverting option prices to obtain implied volatilities. To compute idiosyncratic volatility, we further estimate firm's market beta based on at least 60 prior monthly returns over the rolling window ($t-60$,$t-1$) from the following regression:

$$r_{j,t} = \alpha_j + \beta_j \mathrm{MKT_t} + \nu_{j,t} \tag{A-4}$$

where MKT is the return on the CRSP value-weighted index. The results are similar if we compute market beta based on the Fama-French 3-factor model or through portfolio betas (Fu 2008). To calculate the idiosyncratic portion of implied volatility, we express implied market volatility as a function of market volatility, in a fashion similar to Dennis, Mayhew, and Stivers (2006), such that:

$$\sigma^2_{\mathrm{TV},j,t} = \beta^2_j \sigma^2_{\mathrm{MKT},t} + \sigma^2_{\mathrm{IV_{IVOL}},j,t}, \tag{A-5}$$

where $\sigma^2_{\mathrm{MKT},t}$ is the implied market variance from VIX on day t, $\sigma^2_{\mathrm{TV},j,t}$ is the implied total variance for firm j at time t, β_j is the market beta from the estimation of equation (A-5), and $\sigma^2_{\mathrm{IV_{IVOL}},j,t}$ is the idiosyncratic portion of implied variance for firm j at time t. $\mathrm{IVOL_{OPTION}}$ is defined as the square root of $\sigma^2_{\mathrm{IV_{IVOL}},j,t}$. Theoretically, this value should not be less than or equal to zero, but empirically it is possible. A small number of them have non-positive values and we set these equal to zero. Shown in Table A1, in January, the highest IVOL quintile of stocks on average outperforms the lowest IVOL quintile. Both value- and equal-weighted H−L returns are positive and statistically significant for all five measures. The alphas relative to the Fama-French three-factor model are also positive and statistically significant. Overall, Table A1 shows that the outperformance of highly volatility stocks in January is robust to the choice of IVOL measures.

2 Idiosyncratic skewness

We consider five alternative specification to estimate idiosyncratic expected skewness (EISKEW). The specifications of EISKEW are presented in Table A2. For each measure of EISKEW, we sort stocks based on the December measure into quintiles and compute the mean returns in the following January.

[INSERT TABLES A2 AND A3 HERE]

Shown in Table A3, for all five alternative EISKEW measures, the highest EISKEW quintile on average outperforms the lowest EISKEW quintile in January. The January return differentials between the highest and lowest quintiles range from 9.90% to 13.63%, with significant Fama-French alphas ranging from 5.53% to 9.87%. In other words, our results are insensitive to the specifications to forecast EISKEW.

References

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Table A1: Mean January returns of quintiles based on alternative measures of IVOL

This table reports the average January returns of quintiles sorted based on five measures of IVOL over the period of 1964–2007 for the first four measures and 1997–2006 for the last measure. The five IVOL measures are defined in the appendix. Stocks at the end of December are sorted into quintiles based on IVOL measures and the value- and equal-weighted January portfolio returns are calculated. H−L refers to the hedge portfolio that is long the highest IVOL quintile and short the lowest IVOL quintile. α(HL) refers to the average abnormal return across all Januarys, where abnormal January returns are defined relative to the three-factor model with factor loadings estimated using all monthly returns over the full sample. Newey-West (1987) t-statistics are reported in brackets.

Panel A: Value-weighted					
Rank	$IVOL_D$	$IVOL_W$	$IVOL_{EGARCH}$	$IVOL_{AR(2)}$	$IVOL_{OPTION}$
L (low)	1.45	1.51	2.05	1.75	-0.76
2	2.30	2.17	2.04	2.87	−1.29
3	3.31	2.96	3.68	3.47	−0.24
4	4.03	4.08	4.60	5.84	1.21
H (high)	6.26	6.80	8.58	8.78	4.00
H−L	4.81	5.29	6.53	7.03	4.76
	[4.08]	[4.72]	[4.61]	[5.14]	[2.24]
α(H−L)	1.45	1.99	4.89	5.35	4.08
	[2.30]	[3.06]	[3.14]	[3.67]	[2.21]

Panel B: Equal-weighted					
Rank	$IVOL_D$	$IVOL_W$	$IVOL_{EGARCH}$	$IVOL_{AR(2)}$	$IVOL_{OPTION}$
L (low)	2.63	2.59	2.82	2.42	−0.71
2	3.83	3.79	3.09	3.09	−1.30
3	5.61	5.57	4.61	4.26	−0.21
4	7.70	8.20	6.62	7.01	1.33
H (high)	13.27	13.29	10.80	11.16	4.25
H−L	10.64	10.69	7.98	8.74	4.96
	[5.77]	[6.02]	[5.78]	[5.88]	[2.27]
α(H−L)	7.40	7.39	7.11	7.23	4.18
	[4.61]	[4.72]	[5.13]	[5.02]	[2.30]

Table A2: Monthly cross-sectional regression at the firm level to forecast idiosyncratic skewness

This table reports the results from the monthly cross-sectional regressions of future ISKEW measured over months t through $t+11$ on past ISKEW measured over months $t-12$ through $t-1$, and a set of firm characteristics from July of 1964 through December of 2007. The dependent variable is the idiosyncratic skewness (ISKEW) of weekly returns over month $(t+1, t+12)$. The time series mean of the coefficients from monthly cross-sectional regressions are reported. RET(-1) and RET(-12, -2) refer to the return in the prior month and the prior 2[nd] through 12[th] months, respectively. LOGME is logarithmic firm size, defined as the market equity measured at the end of the preceding month. LOGBM is logarithmic book-to-market equity. Book-to-market equity (BM), from June of year s through May of year $s+1$, is book equity measured at the fiscal year-end through December of year $s-1$, over market equity measured at the end of December of year $s-1$. Share turnover (TURN) is the total monthly trading volume over shares outstanding in the preceding month, multiplied by 100. Trading volume of NASDAQ firms is divided by two. The time series means of the coefficients from monthly cross-sectional regressions are reported with the Newey-West (1987) t-statistics in brackets.

Spec	Intercept	LOGPRC	IVOL (*100)	ISKEW	LOGME	LOGBM (*100)	RET(-1) (*100)	RET($-12, -2$) (*100)	TURN (*100)
I	YES	-0.250	-0.173	0.063					
		[37.84]	[0.77]	[27.34]					
II	YES			0.067	-0.130	1.014	-0.141	-0.138	-0.241
				[32.16]	[54.89]	[3.05]	[9.34]	[14.48]	[4.76]
III	YES	-0.133			-8.877			-0.061	
		[17.07]			[20.35]			[10.45]	
IV	YES		3.061	0.061	-11.711	1.698	-0.195	-0.124	-0.469
			[14.33]	[30.42]	[49.46]	[5.56]	[12.39]	[14.81]	[9.61]
V	YES	-0.125		0.057	-8.176			-0.083	-0.269
		[17.37]		[31.93]	[24.46]			[13.59]	[5.40]

Table A3: Mean January returns of quintiles based on alternative measures of EISKEW

This table reports the average January returns of quintiles sorted on five measures of EISKEW from 1964 through 2007. The five specifications are defined in Table A2. EISKEW is the expected 12-month ahead weekly idiosyncratic skewness based on the firm characteristics observed in December of year $s-1$ and the coefficients estimated in December of year $s-2$ (summarized in Table A2. Stocks at the end of December are sorted into quintiles based on each of the EISKEW measures and both value- and equal-weighted January portfolio returns are calculated. H−L refers to the long minus short portfolio that is long the highest EISKEW quintile and short the lowest quintile. α(H−L) refers to the average abnormal return across all Januarys, where January abnormal returns are defined relative to the three-factor model with factor loadings estimated using all monthly returns over the full sample. Newey-West (1987) t-statistics are reported in brackets.

Panel A: Value-weighted

	Specification to obtain EISKEW				
Rank	I	II	III	IV	V
L (low)	1.47	1.50	1.54	1.50	1.52
2	2.84	3.00	3.17	2.91	3.10
3	4.47	4.84	5.22	4.72	5.00
4	7.33	7.22	7.93	7.27	7.81
H (high)	11.97	11.40	13.03	11.64	12.73
H−L	10.50	9.90	11.49	10.14	11.21
	[5.25]	[6.00]	[5.68]	[5.61]	[5.32]
α(H−L)	6.00	5.53	6.98	5.54	6.42
	[3.83]	[5.18]	[4.41]	[4.42]	[4.14]

Panel B: Equal-weighted

	Specification to obtain EISKEW				
Rank	I	II	III	IV	V
L (low)	1.88	1.90	1.94	1.88	1.79
2	3.33	3.33	3.47	3.24	3.35
3	5.08	5.26	5.28	5.14	5.16
4	7.78	7.94	7.76	7.82	7.94
H (high)	15.18	14.11	14.80	14.44	15.42
H−L	13.30	12.20	12.85	12.56	13.63
	[6.20]	[6.57]	[6.18]	[6.35]	[6.05]
α(H−L)	9.87	8.52	9.47	8.74	9.66
	[4.94]	[5.45]	[4.94]	[5.18]	[4.93]