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Gambling in the Hong Kong Stock Market

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Abstract

This paper documents the existence of a lottery-stock premium in the Hong Kong stock market as reflected by the finding that stocks with stronger lottery features during the current month have poorer future return in the following month. The lottery-stock premium is weaker for stocks with persistent lottery features and is stronger when the overall stock market is more volatile or has poorer returns. In addition, the strength of lottery features can predict the future upside potential of the stock. Overall, this study indicates that people's gambling attitudes affect stock price movements and speculative investors are trading off between the poorer mean return and the better right-hand tail of the return distribution when they are buying the lottery-like securities.

JEL classification: G11, G12

Keywords: Lottery-stock premium, Maximum daily returns, Cross-sectional stock returns

1. Introduction

Although gambling and stock investing are distinct from each other, it is interesting to note that the behavior of gamblers is quite similar to that of speculative investors in the stock markets. On one hand, gamblers are participating in a game that gives them a negative expected return in the hope that they are lucky enough to achieve a positive realized payoff. On the other hand, speculative investors tend to buy those high risk stocks with expected returns that are not commensurate with the risk level. In fact, there exist both theoretical models (e.g., Barberis and Huang, 2008; Mitton and Vorkink, 2007) and empirical studies (e.g., Kumar, 2009; Kumar, Page, and Spalt, 2011; Bali, Cakici, and Whitelaw, 2011) that document the effects of investors' gambling attitude on the outcomes in the stock markets. Studies also suggest that such speculative trading is originated from retail investors (Han and Kumar, 2013) and smaller institutions (Fong and Toh, 2014).

Motivated by the theoretical and empirical studies on the relation between gambling preferences and stock market outcomes on the U.S., this study analyses the behavior of lottery-type stocks on the Hong Kong market by addressing the following four research issues. First, we examine the existence of a lottery-stock premium as reflected by a negative relation between the strength of the lottery features of a stock and its future return. Next, we investigate whether investors' preferences for lottery stocks are different under different stock market and macroeconomic conditions. Third, we assess the rationale for investors to purchase the lottery stocks by studying the relation between lottery features and their ability to predict the future upside potential of the stock. Finally, we investigate whether the persistence of lottery features and people's gambling mentality around the New Year holiday would affect the behavior of the lottery-stock premium.

Following previous studies, we measure lottery features with the following variables: idiosyncratic volatility (*IVOL*), idiosyncratic skewness (*ISKEW*), stock price (*PRICE*), maximum daily return (*MAX*), together with a composite lottery-feature index (*LOTT*) compiled from the above four variables. We use two versions of the *MAX* variable with *MAX*(1) measuring the maximum daily return during the month and *MAX*(5) measuring the average of the five highest daily returns during the month. Our univariate portfolio-level analysis indicates that each of the above measures can independently predict future stock returns. To be specific, a stock's future one-month return is negatively related with its *IVOL*, *ISKEW*, -1 × *PRICE*, *MAX*(1), *MAX*(5) and *LOTT* during the previous month. This finding is consistent with the notion that investors are paying too high a price in buying stocks with strong lottery features such that these stocks suffer from a price correction in the next month. In the firm-level regression analysis that controls for other firm characteristics, all lottery-feature variables except *PRICE* are negatively and significantly related with future stock return when we use only one of them as the lottery-feature variable. On the other hand, only *MAX* and *ISKEW* remain negatively significant when all lottery-feature variables are included in the same regression model.

We find that stock market conditions have impacts on lottery-stock premium. When the overall stock market is more volatile or performs badly, lottery-stock premium increases and there are greater future price corrections of lottery-type stocks. This indicates that investors have stronger preferences of gambling in the stock market when they face a more volatile and poorer market condition. At the same time, we also find evidence that higher aggregate economic activities as reflected by low levels of unemployment rate have positive impact on people's gambling attitude toward the stock market.

We show that the strength of lottery features in the current month can predict the stock's upside potential in the next month where upside potential is measured by future idiosyncratic skewness and future maximum daily return. Therefore, there is a rationale for investors to speculate on lottery stocks even though they earn worse future returns on average. In other words, speculative investors are trading off between the poorer mean return and the better right-hand tail of the return distribution when they are buying these securities. Further, if investors overpay for a stock with strong lottery features in the current month, they will also pay more for the same stock in the coming month if the stock continues to be a lottery-like security. This assertion is confirmed by our regression analysis which shows that the price correction is less economically significant for those stocks with persistent lottery features. Lastly, we do not discover any statistically significant turn-of the-year effects on the lottery-stock premium.

To summarize, this study provides a comprehensive analysis of lottery-type stocks on the Hong Kong stock market. Apart from confirming the existence of a negative relation between lottery features and future stock returns in an out-of-sample setting other than the U.S. and Europe, we present interesting findings which have not been documented in previous studies. In particular, extant researches do not address the effects of persistent lottery features and this is the first study that shows the persistence of lottery features weakens the price correction of lottery-type stocks. Together with the findings that lottery-stock premiums are affected by the overall stock market conditions and that the strength of lottery features are able to predict a stock's upside potential, this study provides us with more understanding about how and why people gambles in the stock markets.

The rest of the paper is arranged as follows. The following section discusses the related literature on lottery-type stocks and develops the testable hypotheses. Section 3 explains the method to identify lottery-type stocks and Section 4 discusses the data. Section 5 presents the empirical results and the final section concludes.

2. Related literature and hypotheses

The effects of investors' gambling preferences on asset pricing can be motivated by the theoretical models of Barberis and Huang (2008) and Mitton and Vorkink (2007). Barberis and Huang (2008) study the pricing of financial securities when investors make decisions according to cumulative prospect theory (Tversky and Kahneman, 1992). Under cumulative prospect theory, people overweight low-probability events and have preference for a positively skewed wealth distribution. Investors thus are willing to pay a high price for a lottery-like security and take an undiversified position in it in order to add skewness to the return on their portfolios. As a result, the positively-skewed security can be overpriced relative to the prediction of the expected utility model and earn a negative average excess return. Using a different model, Mitton and Vorkink (2007) also predict that idiosyncratic skewness will be a priced component of security returns. They assume that investors have same demand for mean and variance but different preference for skewness. They show that investors with greater demand for skewness (the "Lotto Investors") will hold less diversified portfolios than investors with less demand for skewness. In addition, since "Lotto Investors" are willing to trade mean-variance efficiency for upside potential in their portfolios, assets with positive idiosyncratic skewness earn lower returns than assets with negative idiosyncratic skewness.

There are several empirical studies on the pricing of lottery-type securities on the U.S. markets. Kumar (2009) uses price, idiosyncratic volatility and idiosyncratic skewness to measure the strength of a stock's lottery features and defines lottery-type stocks as those low-priced stocks with high idiosyncratic volatility and high idiosyncratic skewness. His idea is that investors looking for "cheap bets" will find low-priced stocks attractive, and similar to lottery tickets, stocks with high idiosyncratic skewness have a relatively small probability of a large payoff. In addition, investors might also believe that the past extreme positive returns are more likely to occur again when idiosyncratic volatility is high. His empirical finding shows that stock portfolios with strong lottery features earn significantly lower average returns relative to stock portfolios with weak lottery features. Kumar, Page, and Spalt (2011) document that individual stocks with stronger lottery features earn lower returns in the cross-section, and the magnitude of such negative lottery stock premium is stronger for firms located in regions of higher Catholic-Protestant ratio. They suggest that their finding is consistent with the conjecture that the gambling propensity is stronger in regions with higher concentrations of Catholics (who are less disapproving of gambling activities) relative to Protestants (who have a stronger moral opposition to gambling).

Bali, Cakici, and Whitelaw (2011) consider stocks with extreme positive returns as lottery-like assets that have a small chance of a large gain and examine the role of extreme positive returns in the pricing of U.S. stocks. Their portfolio analysis and firm-level cross-sectional regressions show a significantly negative relation between the maximum daily return (*MAX*) over the past one month and stock return in the following month. Recently there are several studies confirming the existence of a *MAX* effect in the European stock markets (Annaert, De Ceuster, and Verstegen, 2013; Walkshäusl, 2014; Fong and Toh, 2014). Further, these European studies suggest that the *MAX* effect is strongly dependent on investor sentiment (Fong and Toh, 2014) and stronger among firms with high cash flow volatility or low profitability (Walkshäusl, 2014).

Based on the above studies, this paper provides a comprehensive analysis of the behavior of lottery-type stocks in the context of the Hong Kong stock market. First, we examine whether the prediction of the cumulative prospect theory is applicable to the pricing of Hong Kong stocks. We test this prediction by investigating whether stocks with stronger lottery features tend to have lower expected returns. The first hypothesis is stated as:

H1: There exists a negative relation between the strength of lottery features and future stock return.

Next, we want to investigate whether there is any rationale for investors to purchase the lottery-type stocks even though they are over-priced on average. In the eyes of speculative investors, investing in lottery-type stocks is equivalent to purchasing lottery tickets in the expectation that there is a chance to realize a large positive payoff. If the lottery-type stocks can give large positive potential payoff, speculative investors will still be willing to purchase these stocks even though they earn a lower expected return. Therefore, the purchase of lottery-type stocks can be justified if these stocks are associated with large maximum daily returns and/or large positive skewness in the future. Our second hypotheses are stated as:

H2A: There exist a positive relation between the strength of lottery features and future maximum daily return.

H2B: There exist a positive relation between the strength of lottery features and future idiosyncratic skewness.

Our second hypotheses imply that stocks' lottery features are persistent and carried forward from one period to the next period. As a result, if investors overpay for a stock with strong lottery features in the current month, they will also pay more for the same stock in the next month if the stock continues to be looked like a lottery. In other words, the future price correction will be weaker for those stocks with strong lottery features in both the current month and the next month. This leads to our third hypothesis:

H3: The negative relation between the strength of lottery features and future stock return is weaker for stocks with persistent lottery features.

Previous studies have documented the existence of a turn-of-the-year effect on financial assets with lottery features. Doran, Jiang, and Peterson (2012) find that in the U.S. markets, the out-of-the-money call options which are cheap and have highly skewed payoffs are the most expensive and actively traded in January. In addition, the lottery-type stocks have abnormally high returns in January but tend to underperform in other months. These results suggest that individuals exhibit stronger gambling mentality when they are celebrating the New Year. On the other hand, they also find that lottery-type stocks on the Chinese markets (i.e., stocks trading on the Shanghai Stock Exchange and the Shenzhen Stock Exchange) outperform at the start of the Chinese New Year but not necessarily in January. Doran, Jiang, and Peterson (2012) attribute this finding to the fact that Chinese people celebrate the Chinese New Year more seriously than January 1 and that they also have a tradition to gamble around the Chinese New Year. Overall, their evidence indicates that the gambling preferences of individuals have a positive price impact on securities at the turn of the year.

In Hong Kong, the stock market participants include both overseas investors with western culture and local retail investors with Chinese culture.[1] Therefore, if there exists a turn-of-the-year effect on the lottery-stock premium in Hong Kong, the effect can be applied either to January or the Chinese New Year. During the New Year period, the gambling preference of individuals will stimulate the demand for lottery stocks and cause less important price correction when compared with the non-New Year period. As such, we have the following two hypotheses on the turn-of-the-year effect on lottery-type stocks:

H4A: The negative relation between the strength of lottery features and future stock return is less important in January.

H4B: The negative relation between the strength of lottery features and future stock return is less important in the Chinese New Year period.

3. Identification of lottery-type stocks

Similar to previous studies, we identify stocks with lottery-type features with the following variables: idiosyncratic volatility (*IVOL*), idiosyncratic skewness (*ISKEW*), stock price (*PRICE*) and maximum daily return (*MAX*). We adopt two versions of the *MAX* variable with *MAX*(1) measuring the maximum daily return during the month and *MAX*(5) measuring the average of the five highest daily returns during the month. While *MAX*(1) is the most commonly used measure, *MAX*(5) is less arbitrary and there are studies showing that *MAX*(5) has a stronger effect in determining the return differences between the high *MAX* and low *MAX* stocks (see Bali, Cakici, and Whitelaw, 2011).[2] Therefore, we study

[1] The contribution to total market turnover from local retail investors ranges from 49% in 1999 to 25% in 2008 (Hong Kong Exchanges and Clearing Limited (2010a)). According to the survey conducted by the Hong Kong Exchanges and Clearing Limited (2010b), there are 2.06 million local retail stock investors in 2009 and 85% of them have traded at least once during the twelve months preceding the survey.

[2] Bali, Brown, Murray and Tang (2016) also show that using *MAX*(5) as the lottery measure, investors' demand for lottery stocks is an important driver of the beta anomaly that stocks with high (low) beta are associated with low (high) abnormal returns.

both measures and compare their relative performance in predicting stock returns in the Hong Kong market. In addition to using the above lottery-feature variables independently, similar to Doran, Jiang, and Peterson (2012) and Han and Kumar (2013) we also compile a composite lottery-feature index incorporating the combined effects of *IVOL*, *ISKEW*, *PRICE* and *MAX*. To construct the lottery-feature index (*LOTT*), first we rank our sample stocks into ten groups independently either by *IVOL*, *ISKEW*, -1 × *PRICE* and *MAX*(5). Stocks belonging to the first (tenth) decile group are assigned with the ranking of 1 (10). *LOTT* is calculated as the sum of decile ranks of the above four lottery-feature variables. Using the above definition, stocks with larger value of *LOTT* are considered to be more similar to lotteries.

We measure the strength of each of the lottery-feature variables at the end of each month and examine their impacts to stock returns during the following month. For each stock i, $IVOL_{i,t}$ and $ISKEW_{i,t}$ are estimated by the regression models explained below using daily return data in month t, $PRICE_{i,t}$ is defined as the closing price at the end of month t, and $MAX(1)_{i,t}$ and $MAX(5)_{i,t}$ are the maximum daily return and the average of the five highest daily returns among all the observable daily returns within month t, respectively.

We use the Fama-French (1993) three-factor model to estimate the *IVOL* of a stock:

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_i (R_{m,d} - R_{f,d}) + s_i SMB_d + h_i HML_d + \varepsilon_{i,d} , \tag{1}$$

where $R_{i,d}$ is the return on stock i on day d, $R_{f,d}$ is the risk-free rate on day d, $R_{m,d}$ is the market return on day d, and SMB_d and HML_d are the size and value premiums on day d. To be specific, $R_{m,d}$ is the value-weighted average of all available individual stock returns from Datastream on day d, and SMB_d and HML_d are constructed using the nine (3 × 3) value-weighted portfolios formed on size and book-to-market. SMB_d is the average return on the three small portfolios minus the average return on the three big portfolios and HML_d is the average return on the three value portfolios minus the average return on the three growth portfolios. The component stocks contained in the *SMB* and *HML* portfolios are identified at the end of June in each year and will stay in their respective portfolios for the next twelve months. The risk-free rate is proxied by the yield on the 30-day Exchange Fund Bill (after July 1991) or the 1-month Hong Kong Interbank Offered Rate (before July 1991 when the yields on the 30-day Exchange Fund Bill are not available). The idiosyncratic volatility of stock *i* in month *t* is defined as the standard deviation of the error term $\varepsilon_{i,d}$. We annualize the idiosyncratic volatility measure by multiplying $\varepsilon_{i,d}$ by $\sqrt{250}$.

Following Harvey and Siddique (2000), we estimate *ISKEW* of each stock *i* in month *t* with the two-factor model of excess market return and the squared excess market return:

$$R_{i,d} - R_{f,d} = \alpha_i + \gamma_i (R_{m,d} - R_{f,d}) + \delta_i (R_{m,d} - R_{f,d})^2 + e_{i,d} . \tag{2}$$

The *ISKEW* of stock *i* in month *t* is defined as the skewness of the error term $e_{i,d}$. To ensure that our estimates of *IVOL* and *ISKEW* are reliable, we require each sample stock to have at least 15 daily return observations for estimating equation (1) and equation (2) in each month.

4. Data

The stock-level data used in this study are all collected from Datastream International except that stocks' book values are collected from Worldscope. Although the Datastream data on the Hong Kong stock market starts at early 1980s, the amount of data available for our investigation is rather limited for the whole 1980s. As a result, our sample period starts at January 1990 and ends at December 2012. We include all common stocks from both the "Research" stock list and the "Dead" stocks list in the Datastream database to alleviate the survival bias in the sample.

We employ several procedures to mitigate the potential data problems in the Datastream base. Stock returns adjusted for dividends are computed by the percentage change in stock return index. Since Datastream carries forward the return index from the previous period to the current period in which the stock is not traded, a stock return of zero may be due to no trading rather than to zero change in stock price. To remedy this zero-return problem, we apply the #S filtering to the return index to ensure that only trading period returns are included in our sample. In addition, we correct the data with the screens as suggested by Ince and Porter (2006) and Schmidt et al. (2015). To be specific, if there are no observations in the return variable, then price and dividend (if applicable) information are used to compile the self-created price-based returns if at least price information is available. If the absolute difference between the return index and the self-created price-based returns is greater than 50%, we use the price-based returns to replace the return index. We set the daily return to be equal to 100% (-95%) if the reported daily return is larger (smaller) than 100% (-95%). Further, the return variable is treated as missing if R_t or R_{t-1} is greater than 300% and $(1+R_t)(1+R_{t-1})-1$ is less than 50%. Lastly, we winsorize the monthly returns at the 0.5% and 99.5% levels, i.e., the smallest and largest 0.5% of the observations on the monthly returns are set equal to the 0.5th and 99.5th percentiles, respectively. These procedures enable us to filter out suspicious returns as well as to ensure that our empirical results are not driven by extreme return outliers.

We compute the self-created market value by multiplying the unadjusted price with the number of shares outstanding and set the market value to missing if the difference between the market value reported by Datastream and the self-created market value is greater than 50% in absolute terms. To exclude the so-called "Penny stocks", we delete the monthly observations of a stock if it belongs to the bottom 5 percentile of the distribution of market value in that month. Lastly, we delete the firm-month observations with negative book-to-market ratio. Our final sample consists of 100,258 firm-month observations with non-missing values in all variables used in the empirical analysis.

5. Empirical results

5.1. Descriptive statistics

Table 1 presents the descriptive statistics of the lottery-feature variables and main characteristics of the sample firms. These firm characteristics will be used as the explanatory variables in the regression models to control for other potential factors that may affect stock returns. The definition of the variables is explained in the appendix.

(Insert Table 1 about here)

Panel A of Table 1 shows that our sample stocks have an average (annualized) idiosyncratic volatility of 41.82% and an average (annualized) total volatility of 51.46%. Therefore, on average about 66% of a stock's total variance is firm-specific and the other 34% is related with market movement. The magnitudes of stock volatility on the Hong Kong market are similar to that on the U.S. markets as reported by Ang, Hodrick, Xing, and Zhang (2009) and are larger than that of other developed markets. The statistics of *ISKEW* and *TSKEW* are very close to each other and this indicates that individual stocks' total skewness in daily returns is largely related with their own price movements. On the whole, the five lottery-feature variables of *IVOL*, *ISKEW*, *PRICE*, *MAX*(1) and *MAX*(5) display large cross-sectional variations as reflected in their relatively high standard deviations and inter-quartile ranges.

To understand the relative magnitudes of various lottery-feature variables across different stocks, we sort our sample stocks according to *IVOL*, *ISKEW*, *PRICE*, *MAX*(1) and *MAX*(5) independently in each month and form five portfolios with portfolio 1 containing stocks with the weakest lottery feature and portfolio 5 containing stocks with the strongest lottery feature. Panel B of Table 1 shows the time-series averages of the measures of the respective lottery feature in each quintile portfolio. It is noticed that the average *IVOL* in portfolio 5 is more than three times larger than the average *IVOL* in portfolio 1. On the other hand, the average *ISKEW* in portfolio 1 and portfolio 2 are negative and the average *ISKEW* in portfolio 3 to portfolio 5 are positive. Therefore, not all sample stocks display the right-skewed distribution in daily returns and quite a number of stocks do not possess the lottery-like skewness feature. The last two columns of Panel B indicate that the average *MAX*(1) (*MAX*(5)) ranges from 2.59% (1.58%)

in portfolio 1 to 14.78% (7.27%) in portfolio 5. The magnitudes of the extreme returns in portfolio 5 are quite attractive to the investors if they are able to grasp the chance to realize these returns.

Panel C of Table 1 presents the Pearson correlation coefficients between the lottery measures and various firm characteristics. First we compute the cross-sectional correlation coefficients between various variables in each month. We then calculate the time-series averages of these correlation coefficients together with the robust *t*-statistics based on the Newey-West (1987) standard errors with four lags.

It is not surprised to observe from Panel C that there exist statistically significant correlations among the five lottery-feature variables. In particular, *IVOL*, *ISKEW*, *MAX*(1) and *MAX*(5) are positively correlated among each other and negatively correlated with *PRICE*. While the construction of the two *MAX* variables and *ISKEW* are both related to the tail of the daily return distribution, it is noted that the correlation coefficients between the *MAX* variables and *ISKEW* are smaller than that between *MAX* and *IVOL*. On the other hand, there is no strong correlation between market capitalization (*SIZE*) and *ISKEW* (correlation coefficient = -0.093) while *SIZE* is quite negatively correlated with the other lottery-feature variables. In addition, the book-to-market ratio (*BM*) is not related with *IVOL*, *ISKEW* and the two *MAX* variables as evidenced by their statistically insignificant correlation coefficients. This suggests that the strength of the lottery feature does not depend on whether the firm is a growth firm or a value firm. Finally, we notice that firms with stronger lottery features tend to have larger turnover but at the same time are less liquid according to the Amihud (2002) measure of stock illiquidity (*ILLIQ*). Therefore, although lottery-type stocks are relatively more heavily traded (with respect to number of outstanding shares), investors also face a larger price impact from order flow and incur higher costs in trading these stocks.

5.2. Analysis of lottery-stock premium

Based on the cumulative prospect theory on asset pricing, our first hypothesis predicts that there should be a negative relation between lottery features and future stock returns. We first test this lottery-stock premium hypothesis using portfolio analysis.

Each month we sort our sample stocks independently by the five lottery-feature variables *IVOL*, *ISKEW*, *PRICE*, *MAX*(1), *MAX*(5) as well as the lottery-feature index *LOTT*. The stocks are grouped into five quintile portfolios with portfolio 1 containing stocks with the weakest lottery features and portfolio 5 containing stocks with the strongest lottery features. In addition, we also form a hedge portfolio (i.e., portfolio 5 – 1) by longing stocks in portfolio 5 and shorting stocks in portfolio 1. We form the portfolios based on the lottery measures observed at the end of month *t* and evaluate the returns of the portfolios during month *t+1*. The portfolios are either equal weighted or value weighted by the sample stocks' market capitalization at the end of month *t*. We use both raw returns and risk-adjusted returns to compare the performance of these quintile portfolios. There are studies documenting that the Fama-French (1993) three factor model works well in explaining the portfolio returns in the Hong Kong stock market (e.g., Lam and Tam, 2011). Thus, we regress the portfolio returns on the Fama-French three factors and use the alpha from the three factor model as the measure of risk-adjusted returns. Table 2 presents the monthly averages of these portfolio returns during our 23-year sample period from January 1990 to December 2012 together with the robust *t*-statistics based on the Newey-West (1987) standard errors with four lags.

(Insert Table 2 about here)

One notable pattern observed from Table 2 is that the portfolio returns generally deteriorate with the increase in strength of lottery features. When we measure portfolio performance by raw returns, the portfolios with weaker lottery features always earn positive and highly statistically significant returns. In contrast, the raw returns of the portfolios with the strongest lottery features are either statistically insignificant or marginally significant. Further, the raw returns for the majority of the hedge portfolios are negative though not statistically significant.

The patterns of abnormal returns measured by the 3-factor alphas are similar to the patterns of raw returns of the corresponding quintile portfolios. While the alphas of the weaker lottery-feature portfolios are either positively significant or statistically insignificant, the strongest lottery-feature portfolios and the hedge portfolios have alphas which are all negative and highly statistically significant. The abnormal returns of the strongest lottery-feature portfolios range from -0.70% per month (return of value-weighted portfolio sorted by *ISKEW*) to -2.12% per month (return of value-weighted portfolio sorted by *PRICE*) and the abnormal returns of the hedge portfolios range from -0.65% per month (return of equal-weighted portfolio sorted by *ISKEW*) to -2.25% per month (return of value-weighted portfolio sorted by *PRICE*). All of these abnormal returns are considered to be economically significant. Therefore, our portfolio analysis provides us with evidence that stocks with strong lottery features underperform relative to stocks with weak lottery features. Furthermore, the source of lottery-stock premium is due to the poor returns of the strongest lottery-feature portfolios rather than to the good returns of the weak lottery-feature portfolios. These findings provide the evidence of overpricing correction of lottery stocks.

In addition to portfolio-level analysis, we also conduct firm-level cross-sectional Fama-MacBeth regressions analysis of lottery-stock premium. Compared with portfolio analysis, the cross-sectional regression analysis has the advantage that it can take into account of various firm-specific factors which may affect stock returns. In line with the regression models used by Bali, Cakici, and Whitelaw (2011), Annaert, De Ceuster, and Verstegen (2013), and Walkshäusl (2014), our firm-level cross-sectional regressions take the following form:

$$R_{i,t+1} = \alpha + \beta_L' L_{i,t} + \beta_X' X_{i,t} + \varepsilon_{i,t+1}, \qquad (3)$$

where $R_{i,t+1}$ is stock i's return in month $t+1$, $L_{i,t}$ is a vector of stock i's lottery features observed at the end of month t, $X_{i,t}$ is a vector of stock i's risk factor loadings and firm characteristics observed at the end of month t, $\varepsilon_{i,t+1}$ is the error term, and the βs are the slope coefficients of the regression model. $X_{i,t}$ is used as the control variables other than stock's lottery features that may affect stock returns. To be specific, $X_{i,t}$ includes *MKT_BETA*, *ln*(*SIZE*), *ln*(*BM*), *REVERSAL*, *MOMENTUM*, *ln*(*TURNOVER*) and *ln*(*ILLIQ*) which control for the stocks' exposures to the market risk factor and capture the size effect, book-to-market effect, short-term reversal effect, intermediate-term momentum effect and effects of trading intensity and illiquidity on stock returns. To assess the impacts of various lottery-feature variables, we have eight formulations of $L_{i,t}$ to examine whether each of the lottery measures can individually and jointly predict future stock returns. It should be noted that all the explanatory variables are lagged return predictors with magnitudes which can be observed before the start of month $t+1$.

The Fama-MacBeth estimation results of equation (3) are presented in Table 3. The table reports the time-series averages of the regression coefficients over the 276 months for our sample stocks. Figures in brackets are the robust *t*-statistics based on the Newey-West (1987) standard errors with four lags.

(Insert Table 3 about here)

First we discuss the estimation effects of the control variables. Table 3 shows that after controlling for the effects of the lottery-feature variables, *SIZE* has a negative effect and *BM* has a positive effect on future stock returns, indicating that small-sized firms and value firms have better performance than their counterparts. The coefficient estimates of *REVERSAL* and *MOMENTUM* show that there are both short-term price continuation and intermediate-term price momentum on the Hong Kong stock market. On the other hand, lagged turnover and illiquidity of the stock do not have a significant effect on returns in the next month. Lastly, the risk factor loading *MKT_BETA* is found to be mostly statistically insignificant.

Column (1) to column (6) show that except *ln*(*PRICE*), all other five lottery-feature variables can individually predict future stock returns with the signs consistent with our lottery-stock premium hypothesis. The average coefficients of these five lottery-feature variables are all statistically significant at the 1% level. Combined with the figures of the inter-decile ranges of the lottery-feature variables presented in Table 1 Panel A, these coefficient estimates indicate that when all other stock characteristics remain unchanged, the next month future return will decrease by 0.97% (= -0.017 × (73.460 - 16.401)), 0.56% (= -0.267 × (1.486 - (-0.628))), 1.35% (= -0.112 × (14.568 – 2.473)), 1.80% (= -0.297 × (7.567 – 1.501)) and 0.99% (= -0.043 × (34.000 - 11.000)) if a firm moves from the 10^{th} to the 90^{th} percentile of the distribution of *IVOL*, *ISKEW*, *MAX*(1), *MAX*(5) and *LOTT*, respectively. Column (7) and column (8) present the results when we include *IVOL*, *ISKEW*, *ln*(*PRICE*) and *MAX* in the same regression model. As indicated in column (7), only *MAX*(1) becomes marginally significant when we use all four lottery measures to predict future stock returns. On the other hand, column (8) shows that *MAX*(5) remains highly significant and *ISKEW* is weakly significant. Since *MAX*(5) has the best ability in predicting the cross-sectional variations in stock returns among all simple lottery-feature variables, in subsequent analysis we report only the results of using *MAX*(5) as well as the composite lottery-feature index *LOTT* as our lottery measures.

5.3. Lottery-stock premium in different sub-periods

While Table 2 and Table 3 document the existence of a lottery-stock premium within our whole 23-year sample period, it is interesting to see whether there are changes in the empirical results if we partition the whole period into different sub-periods. In this sub-section we compare the lottery-stock premium between the earlier period and the later period, between the high volatility period and the low volatility period, between the up market period and the down market period, and between the high economic activity period and the low economic activity period. Panel A to Panel D of Table 4 present the sub-period portfolio and regression analyses of lottery-stock premium. For brevity, we report only the average coefficients of *MAX*(5) and *LOTT* when each of them is separately used as the lottery-feature variable in the Fama-MacBeth regressions together with the 3-factor alpha of the hedge portfolio formed by longing stocks with the strongest lottery feature and shorting stocks with the weakest lottery feature. Panel E presents the *t*-statistics for the testing of difference in the average *MAX*(5) and *LOTT* regression coefficients across different sub-periods.

(Insert Table 4 about here)

In Panel A of Table 4, we divide the 1990 – 2012 sample period into two sub-periods of equal length. We find the 3-factor alpha of the equal-weighted hedge portfolio as well as the regression coefficients to be statistically significant in both sub-periods. These results indicate the existence of a lottery-stock premium in both sub-periods and the differences of the monthly Fama-MacBeth regression coefficients between the two periods are either statistically insignificant or barely significant at the 10% level. We also calculate the yearly averages of the regression coefficients and examine their evolution over time. As shown in Figure 1, the average values of *MAX*(5) and *LOTT* are found to be negative for 18 years out of the 23-year period. While we find positive regression coefficients in 1999 and middle 2000s, the overall time-series patterns of the coefficients still indicate the general negative relation between strength of lottery features and future stock returns in the whole sample period.[3]

(Insert Figure 1 about here)

[3] One possible reason for the abnormally large positive regression coefficients in 1999 is that the Hong Kong Government has intervened in the stock market and purchased a considerable amount of blue-chip stocks (equivalent to 7.3% of all the shares in the companies underlying the Hang Seng Index) in late 1998 to drive out speculators. The holding of stocks by the Government might cause a disruption of the relative performance between the blue-chip stocks and lottery stocks in 1999 as public investors were uncertain how the Hong Kong Government would unload its stock holdings. The uncertainty has been resolved when the Hong Kong Government announced in late 1999 that it would unload the shares through the launching of a new Exchange Traded Fund known as the Tracker Fund.

To examine whether stock market conditions would affect the lottery-stock premium, we classify month *t* into high volatility period or low volatility period, and into up market period or down market period, and examine the effects of *MAX*(5) and *LOTT* on stock returns in month *t+1*. To classify the high volatility period and low volatility period, first we divide our sample months equally into three groups according to the value-weighted total volatility of sample stocks in month *t*. Month *t* is defined as high (low) volatility period if the value-weighted total volatility belongs to the top (bottom) tercile or is above (below) 34.30% (25.63%). On the other hand, up (down) market period includes those months in which the value-weighted returns of sample stocks is larger than (smaller or equal to) zero. Panel B of Table 4 shows that most of the 3-factor alphas and regression coefficients are statistically significant in the high volatility period and insignificant in the low volatility period. Panel C shows that all 3-factor alphas and regression coefficients have more negative values and are more statistically significant during the down market period than the up market period. In addition, Panel E indicates the differences of the *LOTT* coefficient between the high and low volatility period and between the up and down market period are both statistically significant at the 5% level. The above results suggest that when the overall stock market is volatile or performs badly in month *t*, investors tend to have larger interests in speculating on lottery-type stocks such that there are greater price corrections in month *t+1*. In other words, investors have stronger preferences of gambling in the stock market when they face a more volatile and poorer market condition.

Panel D of Table 4 classifies whether month *t* has high economic activity as reflected by the employment level in the labor market. We define high economic activity period as those months in which the seasonally-adjusted unemployment rate is below (above) the sample median value of 4.3%. As shown in Panel D and Panel E, there are significant differences in the regression coefficients between the two periods and the lottery-stock premium is found to be stronger when the economy has lower unemployment rate. This suggests that high economic activity has positive impacts on people's gambling attitude toward the stock market. This is different from the findings of Kumar (2009) which discovers that demand for lottery-type stocks actually increases during economic downturns in the United States.

5.4. The predictive power and persistence of MAX(5) and LOTT

Given the fact that lottery stocks are over-priced on average, it is worthwhile to investigate whether there is any rationale for investors to purchase these stocks. As stated in H2A and H2B, the behavior of investors can be justified when there exists a positive relation between stocks' strength of lottery feature and their upside potential measured by future maximum daily return or idiosyncratic skewness. We test these hypotheses with both portfolio and regression analyses.

For the portfolio analysis, at the end of each month *t* we sort our sample stocks by either *MAX*(5) or *LOTT* into five portfolios with portfolio 1 containing stocks with the weakest lottery feature and portfolio 5 containing stocks with the strongest lottery feature. We then calculate the average magnitudes of *MAX*(5) and *ISKEW* for each portfolio during month *t+1*. As shown in Table 5, there is a monotonic increasing relation between the lottery measures in month *t* and the magnitudes of *MAX*(5) and *ISKEW* in month *t+1*. Further, the differences in magnitudes of $MAX(5)_{t+1}$ and $ISKEW_{t+1}$ between the two extreme portfolios are statistically significant at the 1% level, suggesting that the potential future upside payoff of a stock is positively related with its current strength of lottery features. We also run Fama-MacBeth regressions on $MAX(5)_{t+1}$ and $ISKEW_{t+1}$ using $MAX(5)_t$ and $LOTT_t$ separately as the lottery-feature variable together with the lagged control variables used in Table 3. Again, the regression results show that the strength of *MAX*(5) and *LOTT* at month *t* is positively and significantly related with *MAX*(5) and *ISKEW* in month *t+1*.

(Insert Table 5 about here)

The above findings imply that lottery features are persistent and carried forward from one period to the next period. There is another way to examine the persistence of lottery features by looking at the average transition probabilities of *MAX*(5) and *LOTT* where transition probability is the probability that a stock in quintile *i* in month *t* will be in quintile *j* in month *t+1*. The average month-to-month portfolio transition matrix of *MAX*(5) and *LOTT* are shown Panel A and Panel B of Table 6, respectively. As shown in Table 6, if a stock belongs to the strongest *MAX*(5) portfolio in month *t*, there is a 39% chance that it will appear in the same portfolio again in month *t+1*. *LOTT* is even more persistent as there is a 46% chance that a stock will appear in the strongest *LOTT* portfolio for two consecutive months.

(Insert Table 6 about here)

To summarize, our findings indicate that lottery features are persistent and lottery stocks are able to bring investors higher potential payoff. Therefore, investors are tempted to speculate on these stocks even though they earn worse future returns on average. In other words, investors are trading off between the poorer mean return and the better right-hand tail of the return distribution when they are buying these securities.

5.5. Effects of persistence of lottery features on lottery-stock premium

When lottery features are persistent, the continual demand from speculative investors will delay the price correction of the lottery-type stocks. According to our third hypothesis, the negative relation between lottery features and future stock returns should be weaker for stocks with persistent lottery features. To test this hypothesis, we partition the sample stocks equally into two groups according to their strength of lottery features in month *t+1* and estimate equation (3) separately for each group. To avoid potential problems caused by partitioning sample stocks according to similar independent variable of the regression model, to examine the $MAX(5)_t$ ($LOTT_t$) effect on stock returns we use the samples partitioned by $LOTT_{t+1}$ ($MAX(5)_{t+1}$). Since the group of stocks with high $MAX(5)_{t+1}$ or high $LOTT_{t+1}$ are more likely to have strong lottery features carried over from month *t* to month *t+1*, we can test the validity of our hypothesis by comparing the $MAX(5)_t$ ($LOTT_t$) coefficients between the high $LOTT_{t+1}$ ($MAX(5)_{t+1}$) sample and low $LOTT_{t+1}$ ($MAX(5)_{t+1}$) sample.

Table 7 shows that the regression coefficients of $MAX(5)_t$ and $LOTT_t$ are negative and statistically significant at the 1% level in all Fama-MacBeth regressions. Moreover, the estimated values of these two coefficients in the low $LOTT_{t+1}$ and low $MAX(5)_{t+1}$ samples are 50% larger than that in the high $LOTT_{t+1}$ and high $MAX(5)_{t+1}$ samples. We also test the difference of the $MAX(5)_t$ and $LOTT_t$ coefficients between the two samples within the same month and find that the paired *t*-statistic is significant at the 1% level for the $LOTT_t$ coefficient and at the 5% level for the $MAX(5)_t$ coefficient. The above finding is consistent with hypothesis 3 that the negative relation between lottery features and future stock returns is weaker for stocks with persistent lottery features. If investors speculate on the lottery-type stock in the current month, they will also have a larger demand for the same stock in the next month if the stock continues to be looked like a lottery. This causes a smaller price correction of those lottery-type stocks with lottery features that are persistent.

(Insert Table 7 about here)

5.6. The turn-of-the-year effect on lottery-stock premium

Lastly, we examine the existence of a turn-of-the-year effect on lottery-stock premium. As mentioned earlier, individuals may exhibit stronger gambling mentality when they are celebrating the New Year and such behavior will cause less important price correction of the lottery-type stocks during the New Year month. In the case of the Hong Kong market, this effect can occur in January and/or Chinese New Year. Therefore, we have hypothesis H4A on the January effect and hypothesis H4B on the Chinese New Year effect on lottery-stock premium.

We classify the 276 months within our 1990–2012 sample period into 23 January (JAN) months and 253 non-JAN months, or into 23 Chinese New Year (CNY) months and 253 non-CNY months. It is noted that the date of Chinese New Year is based on lunar calendar which usually occurs between mid-January to late-February. To celebrate the festival, the Hong Kong stock market is closed for trading around the Chinese New Year holidays. In our analysis, we define CNY month as the calendar month which has at least five trading days immediately after the Chinese New Year holidays. The rationale for this definition is that if investors have strong gambling preference during the Chinese New Year, their impact on stock prices will be reflected in the early trading days after the stock market holidays. According to the above definition, we use January as the CNY month for 2004 and February as the CNY month for the rest of the sample period.

We divide our whole sample into different sub-samples with $R_{i,t+1}$ equals only either the JAN returns, the non-JAN returns, the CNY returns or the non-CNY returns, and conduct the portfolio and regression analysis of lottery-stock premium for each sub-sample. To test H4A, we compare the effects of *MAX*(5) and *LOTT* on the JAN returns versus the non-JAN returns. Similarly, we compare the effects of *MAX*(5) and *LOTT* on the CNY returns versus the non-CNY returns for the testing of H4B.

Panel A of Table 8 presents the January effect on lottery-stock premium. First, we observe that the 3-factor alpha of the hedge portfolios as well as the coefficients of the Fama-MacBeth regressions for the non-JAN returns are all statistically significant at the 5% level or better. On the other hand, while only the regression coefficient of *MAX*(5) and the 3-factor alpha of the equal-weighted hedge portfolio formed by *LOTT* are statistically significant for the JAN-return, their absolute magnitudes are both larger than their non-JAN counterparts. Therefore, we do not find less important price correction for the lottery-type stocks in January.

(Insert Table 8 about here)

Similar to the case of non-JAN returns, Panel B of Table 8 shows that the 3-factor alpha and the regression coefficients are all significantly negative for the non-CNY returns. In contrast, the 3-factor alpha and the regression coefficients for the CNY returns are all statistically insignificant. Nevertheless, as shown in Panel C, there is no significant difference in the estimated coefficients between the CNY returns and non-CNY returns regressions. One reason for the lack of statistical significance is that the small sample size of the CNY returns regression has lowered the power of the test. As a result, we do not find strong evidence that the negative relation between the strength of lottery features and future stock returns is less important in the Chinese New Year period. Overall, we fail to find the existence of a turn-of-the-year effect on lottery-stock premium in the Hong Kong market.

6. Conclusions

Motivated by earlier studies on the relation between gambling attitude and financial market outcomes, this paper conducts a comprehensive analysis of the lottery-type stocks on the Hong Kong market. We provide the following findings. First, we document the existence of a lottery-stock premium as reflected by the negative relation between lottery features and future stock returns. Second, such negative relation is stronger in a volatile and declining stock market or under better labor market conditions and weaker for stocks with persistent lottery features. Third, the strength of lottery features is positively related with the stock's future upside payoff potential.

The overall interpretation of our findings can be concluded as follows. There is evidence that investors in Hong Kong exhibit gambling behavior which is consistent with the prediction of cumulative prospect theory. They tend to pay too high a price in buying those stocks with strong lottery features. Because the lottery-type stocks are over-priced in the current month, they will earn poorer future returns when there is a price correction in the following month. However, if the stock has persistent lottery features and continues to be looked like a lottery stock, investors will also overpay for the same stock in the next month and weaken the price correction. Moreover, we also show that stocks with stronger lottery features also have better potential for future upside payoff. Therefore, the behavior of speculative investors can be understood as they are just trading off between the poorer mean return and the better right-hand tail of the return distribution when they are buying the lottery-like securities.

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Appendix
Variable definitions

Variable	Definition
$IVOL_{i,t}$	The idiosyncratic volatility of stock *i* in month *t* which is defined as the standard deviation of the daily error term $\varepsilon_{i,d}$ in Eq. (1) multiplied by $\sqrt{250}$.
$TVOL_{i,t}$	The total volatility of stock *i* in month *t* which is defined as the standard deviation of daily returns in month *t* multiplied by $\sqrt{250}$.
$ISKEW_{i,t}$	The idiosyncratic skewness of stock *i* in month *t* which is defined as the skewness of the daily error term $e_{i,d}$ in Eq (2).
$TSKEW_{i,t}$	The total skewness of stock *i* in month *t* which is defined as the skewness of daily returns in month *t*.
$PRICE_{i,t}$	The closing price of stock *i* at the end of month *t*.
$MAX(1)_{i,t}$	The maximum daily return on stock *i* among all its observable daily returns within month *t*.
$MAX(5)_{i,t}$	The average of the five highest daily return on stock *i* among all its observable daily returns within month *t*.
$LOTT_{i,t}$	The lottery-feature index of stock *i* in month *t* which equals the sum of the decile ranks of $IVOL_{i,t}$, $ISKEW_{i,t}$, $PRICE_{i,t}$ and $MAX(5)_{i,t}$ with decile 1 containing stocks with the weakest lottery feature and decile 10 containing stocks with the strongest lottery feature. Stocks with larger value of $LOTT_{i,t}$ are considered to be associated with stronger overall lottery feature.
$MKT\_BETA_{i,t}$	The market factor loading in Eq. (1) for stock *i* estimated with daily returns in month *t*.
$SMB\_BETA_{i,t}$	The size factor loading in Eq. (1) for stock *i* estimated with daily returns in month *t*.
$HML\_BETA_{i,t}$	The value factor loading in Eq. (1) for stock *i* estimated with daily returns in month *t*.
$SIZE_{i,t}$	The market capitalization of stock *i* at the end of month *t*.
$BM_{i,t}$	The book-to-market ratio of stock *i* in month *t* which is measured as the book value divided by the market value of the stock.

Appendix (Cont'd)

Variable	Definition
$REVERSAL_{i,t}$	Short-term reversal as measured by the return on stock i in month t-1.
$MOMENTUM_{i,t}$	Intermediate-term momentum as measured by the cumulative monthly return on stock i from month t-12 to month t-2.
$TURNOVER_{i,t}$	The number of shares traded of stock i during month t divided by the number of shares outstanding at the end of month t-1.
$ILLIQ_{i,t}$	The Amihud (2002) measure of illiquidity of stock i in month t which is defined as the absolute monthly return in month t divided by the respective monthly trading volume in million dollars.

Table 1
Descriptive statistics

The sample period is from January 1990 to December 2012 and consists of 100,258 firm-month observations. Panel A presents the descriptive statistics of the monthly observations of sample stocks. For Panel B, in each month we sort stocks according to five different measures of lottery features (*IVOL*, *ISKEW*, *PRICE*, *MAX*(1) and *MAX*(5)) and form five portfolios with portfolio 1 containing stocks with the weakest lottery feature and portfolio 5 containing stocks with the strongest lottery feature. Figures in Panel B are the time-series averages of the measures of the lottery feature in each quintile portfolio. Panel C reports the Pearson correlation coefficients among the lottery-feature variables and firm characteristics. First we compute the contemporaneous cross-sectional correlation coefficients between various variables in each month and then compute the time-series averages of these correlation coefficients. Figures in brackets are the robust *t*-statistics based on the Newey-West (1987) standard errors with four lags. Definitions of the variables are given in the appendix. ***, **, and * denotes statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Lottery features and firm characteristics

	Mean	Std. dev.	10^{th} pctl.	25^{th} pctl.	Median	75^{th} pctl.	90^{th} pctl.
IVOL (%)	41.812	31.702	16.401	23.407	34.217	50.391	73.460
TVOL (%)	51.461	36.437	21.293	29.708	42.709	62.091	89.567
ISKEW	0.379	0.901	-0.628	-0.154	0.332	0.871	1.486
TSKEW	0.373	0.926	-0.647	-0.165	0.317	0.865	1.496
PRICE (HK$)	6.640	15.236	0.236	0.630	1.790	5.400	16.000
MAX(1) (%)	7.737	7.629	2.473	3.684	5.729	9.143	14.568
MAX(5) (%)	4.135	3.222	1.501	2.201	3.319	5.045	7.567
LOTT	22.009	8.363	11.000	16.000	22.000	28.000	34.000
MKT_BETA	1.004	1.392	-0.237	0.335	0.904	1.558	2.381
SMB_BETA	0.508	1.965	-1.280	-0.413	0.324	1.266	2.492
HML_BETA	0.408	2.363	-1.788	-0.627	0.305	1.382	2.749
SIZE (HK$ billion)	16.682	87.563	0.291	0.631	1.825	6.900	26.163
BM	1.866	9.696	0.229	0.446	0.872	1.601	2.774
REVERSAL (%)	1.999	19.871	-16.010	-7.167	0.000	8.199	20.300
MOMENTUM (%)	31.857	150.054	-52.157	-25.413	7.041	50.154	122.177
TURNOVER (%)	7.753	18.397	0.707	1.566	3.595	8.220	17.723
ILLIQ	0.913	3.922	0.003	0.017	0.099	0.508	1.881

Panel B: Average values of the lottery features in quintile portfolios sorted by the respective lottery feature

Quintile portfolio	*IVOL* (%)	*ISKEW*	*PRICE* (HK$)	*MAX*(1) (%)	*MAX*(5) (%)
1	16.332	-0.755	27.463	2.590	1.582
2	24.860	-0.047	6.206	4.205	2.519
3	32.239	0.325	2.670	5.673	3.307
4	41.992	0.723	1.316	7.770	4.340
5	71.485	1.552	0.509	14.777	7.268

Panel C: Pearson correlation among lottery features and firm characteristics

	ISKEW	*ln*(*PRICE*)	*MAX*(1)	*MAX(5)*	*LOTT*	*ln*(*SIZE*)	*ln*(*BM*)	*ln*(*TURNOVER*)	*ln*(*ILLIQ*)
IVOL	0.222***	-0.425***	0.841***	0.841***	0.734***	-0.388***	0.007	0.300***	0.318***
	[16.99]	[-43.91]	[91.35]	[87.74]	[105.35]	[-39.86]	[0.62]	[17.00]	[26.78]
ISKEW		-0.098***	0.454***	0.334***	0.540***	-0.093***	0.009	0.101***	0.047***
		[12.90]	[55.04]	[44.66]	[82.36]	[-14.26]	[1.44]	[12.33]	[5.68]
ln(*PRICE*)			-0.307***	-0.296***	-0.634***	0.784***	-0.299***	-0.073***	-0.629***
			[-28.31]	[-22.10]	[-90.15]	[66.74]	[-20.44]	[-3.06]	[-46.15]
MAX(1)				0.887***	0.713***	-0.254***	0.005	0.315***	0.190***
				[276.16]	[94.38]	[-23.20]	[0.49]	[19.86]	[13.54]
MAX(5)					0.743***	-0.229***	-0.012	0.387***	0.164***
					[126.01]	[-16.07]	[-0.94]	[22.91]	[9.22]
LOTT						-0.531***	0.105***	0.299***	0.404***
						[-58.95]	[7.81]	[15.96]	[31.11]
ln(*SIZE*)							-0.264***	0.000	-0.811***
							[-23.37]	[0.01]	[-179.08]
ln(*BM*)								-0.081***	0.244***
								[-5.62]	[20.07]
ln(*TURNOVER*)									-0.369***
									[-20.26]

Table 2
Portfolio analysis of lottery-stock premium

This table reports the raw average monthly percentage returns and three-factor alphas (in percentage) of quintile portfolios in month *t+1* sorted by the value of *IVOL*, *ISKEW*, *PRICE*, *MAX*(1), *MAX*(5) and *LOTT* in month *t*. Definitions of *IVOL*, *ISKEW*, *PRICE*, *MAX*(1), *MAX*(5) and *LOTT* are given in the appendix. Portfolio 1 contains stocks with the weakest lottery feature and portfolio 5 contains stocks with the strongest lottery feature. Portfolio 5 – 1 is formed by longing stocks with the strongest lottery feature and shorting stocks with the weakest lottery feature. Value-weighted portfolios are weighted by sample firms' market capitalization at the end of month *t*. The sample period is from January 1990 to December 2012 and consists of 100,258 firm-month observations. Figures in brackets are the robust *t*-statistics based on the Newey-West (1987) standard errors with four lags. ***, **, and * denotes statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Sorted by *IVOL*

	Value weighted		Equal weighted	
Quintile portfolio	Raw average returns	3-factor alpha	Raw average returns	3-factor alpha
1 Weakest	1.468***	0.184**	1.679***	-0.056
	[3.12]	[2.32]	[3.19]	[-0.33]
2	1.520**	-0.208	1.636***	-0.351
	[2.57]	[-1.19]	[2.68]	[-1.46]
3	1.456**	-0.109	1.493**	-0.678**
	[2.46]	[-0.54]	[2.31]	[-2.55]
4	1.384**	-0.504**	1.487**	-0.893***
	[2.19]	[-2.32]	[2.08]	[-3.58]
5 Strongest	1.155	-0.998***	1.410*	-1.112***
	[1.60]	[-3.16]	[1.80]	[-3.96]
5 – 1	-0.312	-1.182***	-0.269	-1.056***
	[-0.67]	[-3.30]	[-0.60]	[-3.91]

Panel B: Sorted by *ISKEW*

	Value weighted		Equal weighted	
Quintile portfolio	Raw average returns	3-factor alpha	Raw average returns	3-factor alpha
1 Weakest	1.488***	0.054	1.673***	-0.349
	[2.85]	[0.27]	[2.81]	[-1.42]
2	1.733***	0.300*	1.551**	-0.590**
	[3.29]	[1.95]	[2.48]	[-2.48]
3	1.522***	0.048	1.684***	-0.485**
	[3.09]	[0.33]	[2.65]	[-2.21]
4	1.211**	-0.377**	1.519**	-0.671***
	[2.18]	[-2.40]	[2.28]	[-3.11]
5 Strongest	1.024*	-0.699***	1.279*	-0.994***
	[1.83]	[-3.10]	[1.80]	[-3.98]
5 – 1	-0.463	-0.753**	-0.395	-0.645***
	[-1.27]	[-2.14]	[-1.62]	[-3.05]

Panel C: Sorted by *PRICE*

	Value weighted		Equal weighted	
Quintile portfolio	Raw average returns	3-factor alpha	Raw average returns	3-factor alpha
1 Weakest	1.458***	0.128**	1.545***	0.018
	[3.01]	[2.29]	[2.95]	[0.16]
2	1.738***	0.168	1.589***	-0.240
	[2.95]	[0.75]	[2.63]	[-1.10]
3	1.282*	-0.820***	1.502**	-0.577**
	[1.87]	[-2.66]	[2.27]	[-2.05]
4	1.387**	-1.047***	1.629**	-0.853***
	[2.03]	[-3.32]	[2.32]	[-3.05]
5 Strongest	0.732	-2.120***	1.423*	-1.456***
	[0.91]	[-6.21]	[1.67]	[-4.42]
5 – 1	-0.726	-2.249***	-0.122	-1.474***
	[-1.27]	[-6.23]	[-0.22]	[-4.94]

Panel D: Sorted by *MAX*(1)

	Value weighted		Equal weighted	
Quintile portfolio	Raw average returns	3-factor alpha	Raw average returns	3-factor alpha
1 Weakest	1.208***	-0.025	1.577***	-0.133
	[2.71]	[-0.16]	[2.99]	[-0.58]
2	1.292**	-0.223	1.734***	-0.245
	[2.21]	[-1.05]	[2.89]	[-1.29]
3	1.702***	0.021	1.650***	-0.532**
	[3.03]	[0.13]	[2.60]	[-2.27]
4	1.744***	-0.004	1.608**	-0.785***
	[2.67]	[-0.02]	[2.24]	[-3.35]
5 Strongest	1.373**	-0.763***	1.133	-1.399***
	[2.00]	[-2.60]	[1.45]	[-4.68]
5 – 1	0.165	-0.738**	-0.445	-1.266***
	[0.39]	[-2.28]	[-1.12]	[-5.20]

Panel E: Sorted by *MAX*(5)

	Value weighted		Equal weighted	
Quintile portfolio	Raw average returns	3-factor alpha	Raw average returns	3-factor alpha
1 Weakest	1.142***	-0.110	1.493***	-0.227
	[2.68]	[-0.59]	[2.92]	[-1.03]
2	1.677***	0.189	1.691***	-0.327
	[2.98]	[1.06]	[2.77]	[-1.45]
3	1.443**	-0.155	1.599**	-0.546**
	[2.42]	[-0.82]	[2.46]	[-2.53]
4	1.630**	-0.183	1.622**	-0.744***
	[2.57]	[-0.67]	[2.34]	[-2.77]
5 Strongest	1.326*	-0.848***	1.293	-1.252***
	[1.86]	[-3.13]	[1.61]	[-4.32]
5 – 1	0.183	-0.738**	-0.200	-1.025***
	[0.38]	[-2.22]	[-0.46]	[-3.90]

Panel F: Sorted by *LOTT*

	Value weighted		Equal weighted	
Quintile portfolio	Raw average returns	3-factor alpha	Raw average returns	3-factor alpha
1 Weakest	1.591***	0.312***	1.631***	0.028
	[3.33]	[3.23]	[3.17]	[0.15]
2	1.374**	-0.169	1.714***	-0.182
	[2.48]	[-0.91]	[2.96]	[-0.93]
3	1.680***	-0.137	1.630**	-0.601**
	[2.78]	[-0.58]	[2.48]	[-2.36]
4	1.231*	-0.772***	1.455**	-0.954***
	[1.83]	[-3.15]	[2.04]	[-3.56]
5 Strongest	0.744	-1.673***	1.292	-1.370***
	[0.92]	[-4.61]	[1.56]	[-4.76]
5 – 1	-0.847	-1.985***	-0.339	-1.398***
	[-1.60]	[-5.04]	[-0.68]	[-5.88]

Table 3
Regression analysis of lottery-stock premium

This table reports the estimation results of the monthly Fama-MacBeth cross-sectional regressions with stock return (in percentage) in month *t+1* as the dependent variable. All the explanatory variables are known at the end of month *t* and definitions of the variables are given in the appendix. The sample period is from January 1990 to December 2012 and consists of 100,258 firm-month observations. The reported figures are the time-series averages of the cross-sectional regression coefficients, with figures in brackets are the robust *t*-statistics based on the Newey-West (1987) standard errors with four lags. ***, **, and * denotes statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	2.099***	1.706***	1.708***	2.059***	2.276***	2.464***	2.175***	2.240***
	[3.59]	[2.85]	[2.71]	[3.52]	[3.94]	[4.86]	[3.43]	[3.52]
$IVOL_t$	-0.017***						-0.001	0.013
	[-2.72]						[-0.13]	[1.17]
$ISKEW_t$		-0.267***					-0.107	-0.180*
		[3.05]					[-1.02]	[-1.91]
$ln(PRICE_t)$			0.071				-0.010	-0.019
			[0.52]				[-0.07]	[-0.14]
$MAX(1)_t$				-0.112***			-0.106*	
				[-2.90]			[-1.76]	
$MAX(5)_t$					-0.297***			-0.385***
					[-3.68]			[-2.74]
$LOTT_t$						-0.043***		
						[-2.82]		
MKT_BETA_t	-0.048	-0.089	-0.067	0.100	0.190	0.032	0.107	0.233**
	[-0.40]	[-0.79]	[-0.59]	[0.75]	[1.54]	[0.30]	[0.76]	[2.00]
$ln(SIZE_t)$	-0.163	-0.159	-0.196*	-0.165	-0.148	-0.220**	-0.244**	-0.217*
	[-1.47]	[-1.38]	[-1.78]	[-1.49]	[-1.29]	[-1.99]	[-2.32]	[-1.92]
$ln(BM_t)$	0.292***	0.316***	0.298***	0.296***	0.296***	0.313***	0.270**	0.271**
	[2.73]	[2.88]	[2.62]	[2.74]	[2.72]	[2.83]	[2.45]	[2.50]
$REVERSAL_t$	0.022*	0.028**	0.021*	0.031**	0.041***	0.028**	0.035**	0.050***
	[1.70]	[2.28]	[1.74]	[2.40]	[2.91]	[2.15]	[2.48]	[3.11]
$MOMENTUM_t$	0.006*	0.007**	0.006*	0.006*	0.006*	0.006*	0.006*	0.006*
	[1.84]	[2.01]	[1.79]	[1.80]	[1.75]	[1.93]	[1.79]	[1.84]
$ln(TURNOVER_t)$	-0.090	-0.184	-0.229*	-0.082	-0.026	-0.096	-0.141	-0.117
	[-0.66]	[-1.31]	[-1.70]	[-0.58]	[-0.18]	[-0.74]	[-1.08]	[-0.87]
$ln(ILLIQ_t)$	0.010	-0.035	-0.024	0.006	0.030	-0.010	-0.036	-0.025
	[0.14]	[-0.44]	[-0.31]	[0.09]	[0.39]	[-0.13]	[-0.53]	[-0.33]
Average R^2	0.146	0.142	0.148	0.148	0.147	0.144	0.175	0.175

Table 4
Sub-period analysis of lottery-stock premium

This table reports the results of portfolio and regression analysis of lottery-stock premium in different sub-periods. We classify month *t* into the earlier period and the later period, the high volatility period and the low volatility period, the up-market period and the down-market period, the high economic activity period and the low economic activity period, and examine the effects of *MAX*(5) and *LOTT* in month *t* on stock returns in month *t+1*. The method of analysis is identical to that reported in Table 2 and Table 3. In the portfolio analysis, the hedge portfolio is equivalent to the Portfolio 5 – 1 of Table 2 which is formed by longing stocks with the strongest lottery feature and shorting stocks with the weakest lottery feature. In the regression analysis, for brevity we do not report the results of the control variables. High (low) volatility period refers to those months in which the value-weighted total volatility of sample stocks is above (below) 34.30% (25.63%). Up (down) market period refers to those months in which the value- weighted returns of sample stocks is larger than (smaller or equal to) zero. High (low) economic activity period refers to those months in which the seasonally-adjusted unemployment rate is below (above) 4.3%. The figures reported in Panel E are the *t*-statistics on the testing of difference in means.***, **, and * denotes statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Earlier period versus later period

	Earlier period (Jan 1990 – Jun 2001)			Later period (Jul 2001 – Dec 2012)		
	3-factor alpha of value-weighted hedge portfolio	3-factor alpha of equal-weighted hedge portfolio	Average regression coefficient	3-factor alpha of value-weighted hedge portfolio	3-factor alpha of equal-weighted hedge portfolio	Average regression coefficient
MAX(5)	-0.739	-0.991**	-0.434***	-0.712	-1.113***	-0.160**
	[-1.54]	[-2.42]	[-3.05]	[-1.43]	[-3.02]	[-2.35]
LOTT	-2.114***	-1.354***	-0.052**	-1.874***	-1.450***	-0.033*
	[-3.82]	[-4.00]	[-2.12]	[-3.08]	[-3.87]	[-1.88]

Panel B: High volatility period versus low volatility period

	High volatility period			Low volatility period		
	3-factor alpha of value-weighted hedge portfolio	3-factor alpha of equal-weighted hedge portfolio	Average regression coefficient	3-factor alpha of value-weighted hedge portfolio	3-factor alpha of equal-weighted hedge portfolio	Average regression coefficient
MAX(5)	-0.751	-1.657**	-0.300***	-0.280	-0.213	-0.139
	[-0.83]	[-2.58]	[-3.01]	[0.57]	[-0.50]	[-0.79]
LOTT	-3.400***	-1.718***	-0.061**	-0.674	-0.773*	0.008
	[3.97]	[-2.89]	[-2.45]	[-1.25]	[1.86]	[0.44]

Panel C: Up market period versus down market period

	Up market period			Down market period		
	3-factor alpha of value-weighted hedge portfolio	3-factor alpha of equal-weighted hedge portfolio	Average regression coefficient	3-factor alpha of value-weighted hedge portfolio	3-factor alpha of equal-weighted hedge portfolio	Average regression coefficient
MAX(5)	-0.026	-0.788**	-0.265***	-1.433**	-1.064**	-0.351***
	[-0.05]	[-2.18]	[-2.73]	[-2.44]	[-2.16]	[-2.79]
LOTT	-1.514***	-1.233***	-0.019	-2.461***	-1.308***	-0.084***
	[-2.92]	[-3.42]	[-1.16]	[-4.34]	[-3.15]	[-4.44]

Panel D: High economic activity period versus low economic activity period

	High economic activity period			Low economic activity period		
	3-factor alpha of value-weighted hedge portfolio	3-factor alpha of equal-weighted hedge portfolio	Average regression coefficient	3-factor alpha of value-weighted hedge portfolio	3-factor alpha of equal-weighted hedge portfolio	Average regression coefficient
MAX(5)	-0.648	-1.146***	-0.502***	-0.988*	-1.132**	-0.088
	[-1.21]	[-2.88]	[-3.85]	[-1.67]	[-2.60]	[-1.15]
LOTT	-1.778***	-1.123***	-0.074***	-1.954***	-1.612***	-0.011
	[-3.66]	[-3.25]	[-4.72]	[-3.14]	[-3.72]	[-0.58]

Panel E: Testing of difference in average regression coefficients across different sub-periods

	MAX(5)	*LOTT*
Earlier period versus later period	1.79*	0.77
High volatility period versus low volatility period	0.80	2.23**
Up market period versus down market period	0.54	2.57**
High economic activity period versus low economic activity period	2.73***	2.53**

Table 5
Portfolio analysis and regression analysis of predictive power of *MAX*(5) and *LOTT*

This table reports the predictability of *MAX*(5) and *ISKEW* in month $t+1$ by *MAX*(5) and *LOTT* in month t. In the portfolio analysis, stocks are sorted into five quintile portfolios with portfolio 1 contains stocks with the weakest lottery feature and portfolio 5 contains stocks with the strongest lottery feature. Portfolio 5 – 1 is formed by longing stocks with the strongest lottery feature and shorting stocks with the weakest lottery feature. In the regression analysis, the dependent variable is regressed on $MAX(5)_t$ and $LOTT_t$ separately as well as on other lagged control variables reported in Table 3. For brevity we do not report the results of the control variables. ***, **, and * denotes statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Predictability of *MAX*(5)

	Average value of $MAX(5)_{t+1}$ in the portfolio sorted by	
Quintile portfolio	$MAX(5)_t$	$LOTT_t$
1 Weakest	2.759	2.599
2	3.291	3.232
3	3.632	3.715
4	4.101	4.201
5 Strongest	5.064	5.113
5 – 1	2.305***	2.514***
	[14.55]	[15.25]

	Average coefficient of the Fama-MacBeth regression using $MAX(5)_{t+1}$ as the dependent variable	
	(1)	(2)
$MAX(5)_t$	0.331***	
	[22.93]	
$LOTT_t$		0.067***
		[14.99]

Panel B: Predictability of *ISKEW*

	Average value of $ISKEW_{t+1}$ in the portfolio sorted by	
Quintile portfolio	$MAX(5)_t$	$LOTT_t$
1 Weakest	0.323	0.260
2	0.340	0.302
3	0.336	0.363
4	0.366	0.404
5 Strongest	0.419	0.454
5 – 1	0.096***	0.194***
	[6.03]	[13.35]

	Average coefficient of the Fama-MacBeth regression using $ISKEW_{t+1}$ as the dependent variable	
	(1)	(2)
$MAX(5)_t$	0.013**	
	[2.01]	
$LOTT_t$		0.004***
		[5.77]

Table 6
Transition matrix of *MAX*(5) and *LOTT*

This table shows the average transition probabilities of *MAX*(5) and *LOTT*. Transition probability is the probability that a stock in quintile *i* in month *t* will be in quintile *j* in month *t+1*. The sample period is from January 1990 to December 2012 and consists of 100,258 firm-month observations.

Panel A: Transition probability of *MAX*(5)

	Portfolio in month *t+1*				
Portfolio in month *t*	1 Weakest	2	3	4	5 Strongest
1 Weakest	0.425	0.230	0.155	0.108	0.082
2	0.238	0.253	0.217	0.169	0.122
3	0.162	0.226	0.232	0.215	0.165
4	0.105	0.180	0.225	0.255	0.235
5 Strongest	0.066	0.115	0.173	0.255	0.392

Panel B: Transition probability of *LOTT*

	Portfolio in month *t+1*				
Portfolio in month *t*	1 Weakest	2	3	4	5 Strongest
1 Weakest	0.512	0.256	0.134	0.073	0.025
2	0.256	0.276	0.228	0.153	0.088
3	0.138	0.230	0.245	0.228	0.160
4	0.071	0.165	0.231	0.274	0.259
5 Strongest	0.021	0.083	0.161	0.274	0.461

Table 7
Effects of persistence of lottery features on lottery-stock premium

This table reports the estimation results of the monthly Fama-MacBeth cross-sectional regressions with stock return (in percentage) in month *t+1* as the dependent variable. In each month *t+1* we separate sample stocks equally into the high *LOTT* group and low *LOTT* group or into the high *MAX*(5) and low *MAX*(5) group and run regressions separately on each group. All the explanatory variables are known at the end of month *t* and are identical to that reported in Table 3. The reported figures are the time-series averages of the cross-sectional regression coefficients, with figures in brackets are the robust *t*-statistics based on the Newey-West (1987) standard errors with four lags. ***, **, and * denotes statistical significance at the 1%, 5%, and 10% level, respectively.

	Stocks with high *LOTT* at month *t+1*	Stocks with low *LOTT* at month *t+1*	Stocks with high *MAX*(5) at month *t+1*	Stocks with low *MAX*(5) at month *t+1*
Intercept	6.987***	0.107	10.345***	1.717***
	[8.57]	[0.25]	[12.49]	[4.03]
$MAX(5)_t$	-0.658***	-0.986***		
	[-5.59]	[-10.95]		
$LOTT_t$			-0.144***	-0.218***
			[-7.31]	[-18.30]
MKT_BETA_t	0.006	0.265	-0.357***	-0.022
	[0.04]	[1.59]	[-2.69]	[-0.16]
$ln(SIZE_t)$	0.272	0.597***	-0.556**	-0.017
	[1.31]	[6.19]	[-2.29]	[-0.17]
$ln(BM_t)$	0.392**	0.199**	0.454***	0.344***
	[2.58]	[2.29]	[3.26]	[4.06]
$REVERSAL_t$	0.085***	0.077***	0.060***	0.054***
	[4.10]	[4.89]	[3.31]	[4.15]
$MOMENTUM_t$	0.010***	0.008**	0.009***	0.006**
	[2.61]	[2.59]	[2.69]	[2.10]
$ln(TURNOVER_t)$	-0.370	-0.167	-0.765***	-0.769***
	[-1.64]	[-1.30]	[-3.11]	[-6.44]
$ln(ILLIQ_t)$	-0.047	-0.115	-0.268	-0.312***
	[-0.32]	[-1.54]	[-1.38]	[-3.88]
Average R^2	0.185	0.259	0.184	0.281

Table 8
January and Chinese New Year effects on lottery-stock premium

This table reports the portfolio and regression analysis of the January and Chinese New Year effects on lottery-stock premium. The method of analysis is identical to that reported in Table 2 and Table 3. In the portfolio analysis, the hedge portfolio is equivalent to the Portfolio 5 – 1 of Table 2 which is formed by longing stocks with the strongest lottery feature and shorting stocks with the weakest lottery feature. In the regression analysis, for brevity we do not report the results of the control variables. Panel A and Panel B report the effects of lagged lottery-feature variables on returns in January and non-January months, and in the Chinese New Year month and non-Chinese New Year months, respectively. The figures reported in Panel C are the *t*-statistics on the testing of difference in means. ***, **, and * denotes statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: January versus non-January returns

	January			Non-January		
	3-factor alpha of value-weighted hedge portfolio	3-factor alpha of equal-weighted hedge portfolio	Average regression coefficient	3-factor alpha of value-weighted hedge portfolio	3-factor alpha of equal-weighted hedge portfolio	Average regression coefficient
MAX(5)	0.336	-1.047	-0.733**	-0.820**	-1.046***	-0.257***
	[0.23]	[-1.32]	[-2.38]	[-2.02]	[-3.47]	[-3.27]
LOTT	-1.321	-1.510*	-0.070	-2.000***	-1.401***	-0.040***
	[-0.97]	[-2.09]	[-1.50]	[-5.05]	[-4.89]	[-3.11]

Panel B: Chinese New Year versus non-Chinese New Year returns

	Chinese New Year			Non-Chinese New Year		
	3-factor alpha of value-weighted hedge portfolio	3-factor alpha of equal-weighted hedge portfolio	Average regression coefficient	3-factor alpha of value-weighted hedge portfolio	3-factor alpha of equal-weighted hedge portfolio	Average regression coefficient
MAX(5)	0.407	-0.814	-0.042	-0.707*	-1.009***	-0.320***
	[0.29]	[-0.70]	[-0.21]	[-1.72]	[-3.33]	[-3.92]
LOTT	0.819	-0.071	0.010	-2.069***	-1.479***	-0.047***
	[0.66]	[-0.07]	[0.21]	[-5.18]	[-5.25]	[-3.69]

Panel C: Testing of difference in average regression coefficients across different sub-periods

	MAX(5)	*LOTT*
January versus non-January returns	1.72*	0.66
Chinese New Year versus non-Chinese New Year returns	1.00	1.28

Figure 1
The yearly averages of the lottery feature coefficients from the monthly Fama-MacBeth regressions