พฤติกรรมการเสี่ยงโชคในตลาดหลักทรัพย์แห่งประเทศไทย

นางสาวอัจฉรา โยมสินธุ์

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GAMBLING BEHAVIOR IN THAI STOCK MARKET

Miss Atchara Yomsin

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Thesis Advisor	Associate Professor Sunti Tirapat, Ph.D.

Accepted by the Faculty of Commerce and Accountancy, Chulalongkorn University in Partial Fulfillment of the Requirements for the Doctoral Degree

.... Dean of the Faculty of Commerce and Accountancy

(Associate Professor Annop Tanlamai, Ph.D.)

THESIS COMMITTEE

....Chairman

(Associate Professor Seksak Jumroenvong, Ph.D.)

....Thesis Advisor

(Associate Professor Sunti Tirapat, Ph.D.)

....Examiner

(Associate Professor Charlie Charoenwong, Ph.D.)

....Examiner

(Associate Professor Sothitorn Mallikamas, Ph.D.)

....Examiner

(Anant Chiarawongse, Ph.D.)

....External Examiner

(Associate Professor Kamphol Panyagometh, Ph.D.)

อัจฉรา โยมสินธุ์: พฤติกรรมการเสี่ยงโชคในตลาดหลักทรัพย์แห่งประเทศไทย (GAMBLING BEHAVIOR IN THAI STOCK MARKET)
อ.ที่ปรึกษาวิทยานิพนธ์หลัก: รศ. ดร.สันติ ถิรพัฒน์, 123 หน้า

วิทยานิพนธ์ฉบับนี้ศึกษาพฤติกรรมนักลงทุนในตลาดหลักทรัพย์แห่งประเทศไทยในช่วงเดือนมกราคม พ.ศ. 2542 ถึงเดือนธันวาคม พ.ศ. 2551 พฤติกรรมที่พบเห็นโดยทั่วไปในการเล่นการพนัน การซื้อลอตเตอรี่ การชอบเสี่ยงโชคและพฤติกรรมการลงทุนที่ไม่สมเหตุสมผลเป็นแรงจูงใจสำคัญของการศึกษาวิจัยนี้ ผู้วิจัยใช้เครื่องมือเพื่อวัดพฤติกรรมการซื้อขายหลักทรัพย์ของนักลงทุนหลายวิธี และพบว่านักลงทุนรายย่อยในตลาดหลักทรัพย์แห่งประเทศไทยชอบซื้อขายหุ้นที่มีลักษณะเหมือนลอตเตอรี่ (หุ้นที่มีราคาต่ำ มีความผันผวนและความเบ้เฉพาะตัวสูง) มากกว่านักลงทุนสถาบันและนักลงทุนต่างชาติ นอกจากนี้ นักลงทุนรายย่อยมีความต้องการซื้อหุ้นที่มีลักษณะเหมือนลอตเตอรี่ในช่วงที่เศรษฐกิจไม่ดีซึ่งเป็นพฤติกรรมที่คล้ายกับการซื้อลอตเตอรี่และการพนันในรูปแบบอื่น ผู้วิจัยยังพบด้วยว่าพฤติกรรมการลงทุนแบบเสี่ยงโชคของนักลงทุนรายย่อยส่งผลกระทบทางลบต่อพอร์ตการลงทุน จากการวิเคราะห์การเสี่ยงโชคในช่วงเวลาที่แตกต่างกัน พบว่านักลงทุนรายย่อยมีความต้องการซื้อหุ้นที่มีลักษณะเหมือนลอตเตอรี่มากกว่าปกติในเดือนมิถุนายน ส่วนนักลงทุนสถาบันมีความต้องการซื้อหุ้นที่มีลักษณะเหมือนลอตเตอรี่มากกว่าปกติในเดือนธันวาคม สำหรับความต้องการซื้อหุ้นที่มีลักษณะเหมือนลอตเตอรี่ของนักลงทุนต่างชาติไม่มีความแตกต่างกันในแต่ละช่วงเวลา จากการวิเคราะห์ผลตอบแทนของหุ้นที่มีลักษณะเหมือนลอตเตอรี่ด้วยวิธี GJR-GARCH แสดงให้เห็นว่าหุ้นที่มีลักษณะเหมือนลอตเตอรี่จะให้ผลตอบแทนสูงกว่าปกติในเดือนมิถุนายนและเดือนธันวาคม ซึ่งสอดคล้องกับความต้องการซื้อหุ้นที่มีลักษณะเหมือนลอตเตอรี่ของนักลงทุนรายย่อยและนักลงทุนสถาบันในเดือนมิถุนายนและเดือนธันวาคม การศึกษาพฤติกรรมการเสี่ยงโชคในการลงทุนนี้แสดงในเห็นมุมมองใหม่ๆ เพิ่มเติมจากแนวคิดดั้งเดิมในการศึกษาเรื่องความผิดปกติของผลตอบแทนจากการลงทุนในหลักทรัพย์

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This dissertation investigates investor's gambling behavior in the Thai stock market during sample period between January 1999 and December 2008. This study is motivated by the anecdotal evidence of prevalent lottery participation, gambling activity and evidence of behavioral bias in trading decisions. Using several measures of investor trading activity, we find that retail investors exhibit stronger preference in lottery-like stocks (low priced stocks with high idiosyncratic volatility and skewness) than institutional and foreign investors do and their propensity to invest in lottery-like stock increases during the economic recession which is similar to demand in lottery tickets and other gambling activities. Our evidences show that retail investor gambling-motivated decision negatively influences their portfolio performance. Our analyses on the gambling seasonality indicate that retail investors demand more of lottery-like stocks in June while institutional investors demand more of lottery-like stocks in December. Foreign investors do not exhibit any difference in demand level for lottery-like stocks during different time periods. Our findings from GJR-GARCH model display the significantly positive return of lottery-like stocks in Junes and Decembers. As evidences by our bivariate vector-autoregression analysis, positive lottery-like stock returns seasonality in June is corresponding with retail investors' demand of lottery-like stocks in June and returns seasonality in December is corresponding with institutional investors' demand of lottery-like stocks in December. This gambling effect provides new insight into the conventional anomalous seasonality in stock return, the gambling seasonality.

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Student's Signature Atchara Yomsin

Advisor's Signature Sunti Tirapat

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CHAPTER I
INTRODUCTION

The Efficient Market Hypothesis (EMH) assumes that all investors are rational and ignores an involvement of human behavior in the analysis. While the EMH discusses how people should behave based on rational utility maximizing, when people do not behave rationally, this theory may not be put up as a better explanation (Hirshleifer (2001)). Since time and cognitive resources are limited; investors may not optimally consider all information needed for making decision and they may be unable to solve complex investment problems and rely on heuristics instead. Recently, finance literatures evidence that individual investors are particularly exposed to behavioral bias that weakens their ability to make rational investment decisions and this bias is stronger in a situation where firm-specific uncertainty is very high (Coelho and Taffler (2009)).

One exciting trading behavior that cannot well explained by traditional finance theory is individuals' participation in lottery. People tend to place high subjective valuations on low probability events, which exhibit gambling preferences with positively skewed payoffs. When an individual buys a lottery he or she spends a small amount of money and expected to earn a low negative return with a high probability and a large positive return with a very small probability. Comparatively, investor in the stock market may hold riskier portfolio because they are risk-seeking or they may want to have a positive probability, even though very small, of reaching their aspiration levels. They may know that some risks are worth taking and demand assets that have lottery-like features. As Shleifer and Summers (1990) argue that some investors are not fully rational and their demand for assets is shaped by beliefs and sentiments that are not fully justified by fundamental information. It would be valuable to understand whether individual investor's trading motives are rooted in behavioral hypothesis. Since lottery players and stock traders are similar in many aspects and relate much about the deviation from conventional expectation. In Thailand, on average, government lottery ticket returns about 60 Baht to players for a 100 Baht wager (Panitkijkosol (2004)). This relatively large negative expected return does not appear to have reduced Thai individuals participate in lotteries at all. In 2000, National Economic and Social Development Board reported that 62.49 percent of Thai people participate in government lottery and 71.82 percent involve in an illegal underground lottery. Gambling involves a vast amount of money and a large number of people (Phongpaichit, Piriyarungsan, Treerat, and Keawthep (1999)). Rich people's behavior is not different, but their gambles do take a different shape and form. Rich people invest in sophisticated financial instruments that similar allow them to preserve capital and gamble with only a small fraction of their money Shefrin and Statman (2000), Shiller (2003), Statman (2002), and Kumar (2009) have emphasized the role of gambling behavior in the context of investment decisions. The stock market may be attractive for investor who belief that they are outperform the market, mostly overconfident investors. The lottery-like stock, stock with lower price, higher volatility, and large positive skewness features, is likely to be most influenced by gambling motivation.

Furthermore, evidences from gambling and individual risk taking suggest that investors may exhibit different mentality in different period of time. They may not gamble all the time. For example, Thaler and Johnson (1990) finds that people tend to engage in risk seeking activities after experiencing outcome payoffs in prior rounds of gambling. Doran, Jiang, and Peterson (2009) shows that investors exhibit stronger gambling mentality in the New Year. Barberis and Huang (2008) find that investors have a predisposition towards selecting stocks with lottery features at the turn of the year. These stocks perform well in January but underperform for the remainder of the year. Kumar (2009) indicates that investors' propensity to buy lottery ticket and lottery-like stock increase when economic conditions are relatively less favorable. Johnson and Tversky (1983) address that moods have impact on decision even the cause of the mood is unrelated. Edmans, Garcia, and Norli (2007) shows that sporting events in general impact human behavior. They find a significant strong negative stock market reaction to losses by national football teams.

Motivated by the observable fact of government lottery participation, the widespread gambling activity, individual risk taking in Thailand, and the existing evidences of behavioral bias in trading decision of retail investors, we conjectures that retail investors likely to place aggressive trades on lottery-like stocks, relative to other types of investors, due to their behavioral biases and their gambling preferences. Our study aims to extend a behavioral finance literatures by (i) examining whether retail investor's trading motives are influenced by gambling preferences, and (ii) investigating whether there is the gambling seasonality in Thai stock market. Since the majority of investors (by value and number) in Thai stock market are retail investors, their behavioral bias may affect the stock prices.

This study contributes to a growing literature in behavioral finance in several ways. Firstly, the transactional dataset of the Stock Exchange of Thailand provides in detail the trading and transactions of all participants in the market. This data set offers a clear identification of which investor types trades the stock. It is useful to analyze a data set that describes how all market participates behave to characterize both the similarities and heterogeneity of investors. This data set helps us to obtain the actual trading pattern of different investor types, rather than using a proxy. The outstanding richness of these data allows a uniquely detailed examination of the trading behavior of retail, institutional, and foreign investors. Combining with the high levels of retail investor involving in Thai stock market relative to other developed markets, we offer a good out-of-sample test that complements a behavioral finance literature that concentrates in the developed stock markets.

Secondly, we incorporate the gambling mentality into the trading analysis to show that retail investors, not institutional or foreign investors, are more exposed to behavioral bias. This evidence allow us to add to the growing behavioral finance literatures that reveals retail investors are more vulnerable to behavior bias than institutional and foreign investors (for example, Odean (1999), Barber and Odean (2000), Seasholes (2000), Grinblatt and Keloharju (2000), Barber and Odean (2001), Froot and Ramadorai (2001), Barber, Odean, and Zhu (2005), Hvidkjaer (2006), Barber, Lee, Liu, and Odean (2006), Barberis and Huang (2008)). Specifically, we offer an alternative explanation for the underperformance of retail investors.

Thirdly, we attempt to expand the conventional anomaly in finance literature by linking the well known seasonal anomalies (i.e. Monday effect, January effect, and the Calendar effect) and investors' gambling-motivated trading. Since investors have a propensity to change their risk-taking tendency when decisions are framed in multi-period setting, the demand for gambling may also different for each period of time. Our results show that retail investors reveal their time-variation in demand of lottery-like stocks. Finally, we employ the more developed econometric technique, the GJR-GARCH model to investigate the relationship of stock returns and behavioral factors. Our results evidence the positive return seasonality in lottery-like stocks in June and December. This gambling seasonality appears to be evidence against the Efficient Market Hypothesis.

We exploit investors trading data of all individual stocks traded on the Stock Exchange of Thailand (SET) over the sample period form January 1999 to December 2008. Using several measures of investor trading activity, we find that retail investors exhibit the stronger preference for lottery-like stocks than institutional and foreign investors and their propensity to invest in lottery-like stocks increases during the economic recession which is similar to the demand in lottery tickets. We evidence that retail investor gambling-motivated decision negatively influences their portfolio performance.

Our analyses on the gambling seasonality indicate that retail investors demand more of lottery-like stocks in June while institutional investors demand more of lottery-like stocks in December. In contrast, foreign investors do not exhibit any difference in demand level for lottery-like stocks during different periods of time. The potential explanation for institutional investors' high demand in lottery-like and nonlottery-like stocks in December is the buying pressure form the tax-deductible fund, namely RMF (Retirement Mutual Fund) and LTF (Long-Term Equity Fund) as the year end is approaching. Thai investors (around 70 – 75%) often buy into the LTF and RMF funds in the forth quarter of the year, while most choose to invest in December (KE live research (2010)). According to the Association of Investment Management Companies, net new fund flow into the LTF in December is 86.66% of the total net new fund flow in 2010, (69.27% in

2009) while the net new fund flow into the RMF in December is 60.87% of the total net new fund flow in 2010 (68.38% in 2009).

Our investigations on the market anomaly suggest that selling pressure from retail investors can be the source of Monday anomaly in Thai stock market but there is no evidence of gambling demand on Monday. Results from the bivariate vector-autoregression (VAR) model evidence the positive dynamic relation between retail and institutional investors' BSI and the lottery-like stock returns. Interestingly, our findings from GJR-GARCH model display the significantly negative return of lottery-like stocks in Non-January month and the positive returns of lottery-like stocks in June and December. Concerning that there are the dynamic relation between investor sentiments and lottery-like stock returns, the positive returns seasonality are corresponding with the retail investors' high demand of lottery-like stocks in June and with the institutional investors' high demand of lottery-like stocks in December. We conjecture that retail investors cause return seasonality in June due to their behavioral bias, i.e. illusion of control. This gambling seasonality appears to be another piece of evidence against the Efficient Market Hypothesis.

The remainder of this study is structured as follows. Chapter II reviews the related literature. Chapter III discusses our research hypothesis. Chapter IV describes the data used in this study and the variable construction. Chapter V presents our research methodology. Chapter VI reports our empirical findings and conclusion is provided in Chapter VII.

CHAPTER II
LITERATURE REVIEW

This chapter presents an overview of related literatures. Starting from a investor behavior in the stock market and empirical evidences of their behavior, follow by the investor's gambling preference related evidences. In order to explore the gambling behavior of retail investors closer, lottery-like stock literatures are reviewed for the reason that lottery-like stock can be viewed as a stock that are likely to be most affected by investor sentiment, in particular it can perceived as a gambling device in the stock market. Then, the psychological characteristics under different time period of investor literatures are summarized.

2.1 Investor Trading Behavior

In the traditional finance theory, the Efficient Market Hypothesis (EMH), investors are assumed to process new information correctly and make decisions that are normatively acceptable (Barberis and Thaler (2005)). Investors must be able to consider many pieces of information relating to assets and must fully understand the future consequences of all their actions. Additionally, financial markets must be frictionless that security prices reflect their fundamental value and the influences of irrational investors are corrected by rational arbitrageurs. According to this EMH, market is efficient if prices always fully reflect available information. In this market, stock market return is unpredictable and there is no trading pattern which an investor can follow in order to create the profit opportunities. However, there are numerous empirical evidences identifying patterns in stock returns or the market anomalies that were completely unexpected under the EMH.

In reality, investors do not posses all of these rational characters. They fail to update beliefs correctly and have preferences that differ from rational investors (Kahneman and Tversky (1979)). Moreover, rational investors are bounded in their possibilities, or may even be absent such that markets will not always correct non-rational behavior (Barberis and Thaler (2005)). Tversky and Kahneman (1992) concluded in their paper that people have in many ways that systematically violate the axioms of rational behavior under uncertainty. In particular, retail investors are vulnerable to cognitive biases.

The recent empirical studies on retail investors have documented a number of behavioral biases. For example, small investors are more subject to cultural and language biases (Grinblatt and Keloharju (2000)). Retail investors are influenced excessively by familiarity and salience (Barber and Odean (2000)). They trade to reduce regret (Barber, Lee, Liu, and Odean (2006)). They are vulnerable to errors in evaluating risk (Barberis and Huang (2008)). They are slow to incorporate information into prices. They are overconfident and overconfidence leads to excessive poor trading (Barber and Odean (2000)). Barber, Odean, and Zhu (2005) use retail investors as their proxy for noise traders. They conclude that noise traders create the stock price deviation. Odean (1999) also shows that trades of many investors not only fail to cover transaction costs, but tend to lose money before transaction costs.

Additionally, Hvidkjaer (2006) finds that those stocks most actively buy by retail investors underperformed in the following year and continue underperformance for up to three years. Perhaps retail investors enjoy trading and receive utility from playing with their investment; even though they lose. Benartzi and Thaler (2001) show evidence of irrational investor where investors follow a “1/n” allocation rule across investment choices regardless of the stock-bond mix of the available choices.

In the related line of studies, an investor is said to be informed if he can arrive at reliable conclusions about whether assets are fundamentally overvalued or undervalued. Investors have different capabilities and speed to acquire and process information. Informed investors know intrinsic values better than uninformed investors because they have better access to information and can better evaluate the implication from their information. Kyle (1985) shows that informed investors benefit from their private information by gradually revealing their information through trade. Informed investors profit on private information, while uninformed investors incur losses. Correspondingly, Fama (1998) point out that, for the strong version of EMH to hold, information and trading cost must be zero. Otherwise, some investors can attain costly information for greater returns while uninformed investors receive lower returns. It is difficult to explicitly identify informed and uninformed investors ex-ante. Observably, many finance studies presume that, on average, retail investors are less informed and less professional skill in processing information than institutional and foreign investors. They also cannot devote full time to monitor market and cannot form a correct interpretation of the signal even they know that the signal exists.

With the important role in managing other people's money, their full time to monitor the market, and their professional skill, institutional investors are more efficient than retail investors in analyzing the information and they have incentive and volume to make it economical in acquiring expensive information and technology. Institutional investors often have access to information system and news that allow them to achieve a better understanding of not only the firms but also the macroeconomic conditions (Grossman and Stiglitz (1980), Barclay and Warner (1993), and Chakravarty (2001)). They can create the better quantitative models from underlying information. This significantly lessens the impact of one person's biases on the investment decision.

It seems also reasonable to believe that foreign investors tend to do better than individual investors. Since foreign investors usually have superior skill, better experience and sophisticated technology for information processing. Seasholes (2000) examines the daily returns of foreign portfolio in Taiwanese stock market and finds that foreign investors generate above risk-adjusted returns. Foreign investors also buy prior to positive and sell prior to negative earning surprises in this study. In a similar vein, Grinblatt and Keloharju (2000), and Froot and Ramadorai (2001) support the notion that foreign investors are generally better investors since they are informed investors. They evidence that foreign investors outperform domestic investors.

However, more recent researches have evidenced that some retail investors are more informed or skilled than other. Choe, Kho, and Stulz (2005) investigate whether domestic investors have an edge over foreign investors in trading domestic stocks. Using Korean data, their results show that foreign money managers pay more than domestic money managers when they buy and receive less when they sell for medium and large trades. They find some evidence that domestic retail investors have an edge over foreign investors. Also, foreign investors may be at greater informational disadvantages in small stocks, which have low analysts and media coverage, and in growth firms, where the accounting information is a less important driver of firm value. Dvorak (2005), using transaction data from Jakarta Stock Exchange, find that foreign investors systematically buy at higher and sell at lower intraday price than domestic investors, foreign investors tend to sell prior to large positive returns and the permanent impact of foreign purchase is smaller than that of domestic purchases. These findings lead to the conclusion that domestic investors have an information advantage over foreign investors. Nevertheless, the empirical evidence on the issue that who has the information advantage is inconsistent.

Collectively, a large body of literature shows that investors are limited in their ability for processing information and are limited in their attention capacity. They are prone to variety of beliefs that deviate from the belief of rational agents. They are indeed unable to deal with the finance decisions in the way traditional finance theory prescribes. These behaviors may yield biases in financial markets. Thus, it is necessary to allow the possibility that all investors are not always fully rational since most economists recognize the extreme version of EMH as unrealistic.

2.2 Lottery-like Stock

A fascinating trading activity that cannot well explained by traditional finance theory is individuals' involvement in lottery. People tend to place high subjective valuations on low probability events, which exhibit gambling preferences with positively skewed payoffs. When an individual buys a lottery he or she spends a small amount of money and expected to earn a low negative return with a high probability and a large positive return with a very small probability. Relatively, investor in the stock market may hold riskier portfolio because they are risk-seeking or because they want to have a positive probability, even though very small, of reaching their aspiration levels. They may know that some risks are worth taking and demand assets that have lottery-like features. According to Kumar (2009), lottery-like stocks would have lower prices, higher volatility, and large positive skewness features. Barberis and Huang (2008) show that in an economy with cumulative prospect theory investors, low probability events are overweighed and securities that have positively skewed returns can be overpriced in the short run and earn low returns in the long run. The probability weighting leads investors to prefer positive skewness in individual securities. They conjecture that securities with lottery features are expected to earn lower average returns because investors are willing to accept lower average returns for a small probability of a large potential gain.

Consistent with this hypothesis, Kumar (2009) find that lottery-like stocks earn lower average return. In a similar vein, Bali, Cakici, and Whitelaw (2008) investigate the significance of extreme positive returns in the cross-sectional pricing of stocks. They document a statistically and economically significant relation between lagged extreme positive returns, as measured by the maximum daily return over the prior month, and future returns. They interpret their results in the framework of a market with poorly diversifies investors who have a preference for lottery-like assets. Thus, expected returns on the stocks with high idiosyncratic risk that exhibit extreme positive returns are low.

2.3 Lottery Buyer and Stock Trader

Friedman and Savage (1948) state that people who buy insurance policies often buy lottery tickets as well. Since they hope a lottery ticket will lift them into a higher social class while they trust that an insurance contract will protect them from falling into a lower social class. Behavioral bias (i.e. illusion of control) leads people to think that they can predict the future better than they actually can and to act as if they can control random events. The illusion of control leads lottery players to believe that their chosen better numbers and it leads stock traders to believe that their chosen better stocks.

Perhaps this is because everyday life involves risk and chance. Gambling activities transform these risks into a manageable, finite thing—a game. Understanding the rules of the game, the amount of risk, and the stakes, people can make a choice whether to engage in the activity. Hopes of winning money, the adrenaline rush of the unknown or leisurely fun entice people to gamble. Gamblers may be risk-averse, but they are also attracted to the positive skewness of returns offered by low probabilities and high-variance bets. Christiansen (1987) estimated that lottery winners receive, on average, 49 cents of every dollar paid by all ticket buyers. The expected return of a lottery tickets is a 51 percent loss. Lottery buying is a negative-sum game. Some win, some lose, but the total amount that winners receive is less than the total amount that losers pay. Because of lottery administrators take some of the money. Stock trading also is a negative-sum game. But the frame of stock trading is not clear.

According to Statman (2002), lottery playing and stock trading are common in practice, but they are puzzles in traditional financial theory. Lotteries are puzzles because, according to standard financial theory, people are averse to risk; they are willing to take risks only on investments that offer sufficiently high expected returns. Stock trading is a puzzle because a trader's offer to trade should raise suspicion in fellow traders that the would-be trader has superior information. Therefore, rational traders should refuse to trade under such conditions, and no trading will take place.

Statman propose that lottery players and stock traders are similar in many characteristics. Firstly, they, both, think that they are above average. Secondly, they have aspirations to be millionaires and stock trading and lottery buying offer the chances. Thirdly, they have emotions. Hope and fear may be the strongest emotions that drive lottery players and stock traders. Lastly, they like to play. Although lotteries and stocks offer a different return structure, different level of complexity, and different values. These provide the sense that skill is exercised. In summary, the behavior of stock traders and lottery buyers are similar in many features and reveal much about the deviation from rational expectation and traditional finance theory. It is motivating to study whether the gambling attitudes carry over into stock market investing decision.

2.4 Gambling Preference and Lottery Participation

In accordance with cumulative prospect theory (Tversky and Kahneman, 1992), people are generally risk seeking for options that have a low probability on a high gain or a high probability on a small loss. By contrast, they are risk averse for options that have a high probability on a low gain or a low probability on a big loss. Many empirical researches document the individuals' preference to gamble as an explanation for individual financial decision makings, such as the purchase of insurance and lotteries, portfolio under diversification, and portfolio overweighting on lottery-type stock. Gambling refers to the activity where an individual takes large risks but the reward is not corresponding with the level of risk taken. Gamblers still undertake the bets because they derive utility from the excitement of being in risky situation. Cook and Clotfelter (1993) propose that the popularities of Lotto in the United States results from players' being more sensitive to the large jackpot than to the correspondingly probability of winning. Their regressions show that across states, lottery tickets sales are strongly correlated with jackpot size. Within a state, ticket sales each week are strongly correlated with the size of the rollover. In expected utility theory, this can be explained by utility functions that are convex. Prospect theory easily explains the demand for high jackpots by overweighting of very low probabilities.

Faustino, Kaizeler, and Marques (2009) state that there are more gamblers than non-gamblers in every society, which leads to the consideration that the act is normal in itself. Leerattanakorn (2004) documents that 54 to 68% of people in the U.S. involve in gambling and 80 to 94% of people in the U.K and 81 to 92% of people in Australia do. While Barber, Lee, Liu, and Odean (2006) note that the total lottery gambling sales in Taiwan is at least 6.74% of the GDP in Taiwan. The U.K. lottery operator accounts for over 70% of the total U.K. population plays the lottery regularly. Gambling might very well be seen as functional to a society. Gambling gives excitements and emotions that animate society and assures social stability, fulfilling needs, and helping to release pressure and stress. Gambling can be considered a shock absorber, acting as a social safety value. Lotteries are recreational but can also be addictive and compulsive. Social frustration may lead to gambling in a search for control and exciting experiences. Motivational factors behind lottery gambling may be classified into two broad categories, personal and environmental factors. Among personal factors, education, beliefs about skill, luck and optimism were found to relate significantly with lottery gambling. Environmental factors have been defined as lottery play by family and friends, the role of mass media such as newspaper and televisions (Ariyabuddhipongs and Chanchalermporn (2006)). Observably, lottery gambling and stock investing is similar in, at least, two ways. Both decisions are involving money and are situations in which people make decisions under risk.

The stock market, with a fair mix of chance and skill, is likely to be perceived as an attractive setting for gambling. Particularly, people who are overconfident may have a stronger belief that they can outperform the market and they are likely to exhibit strong preference for lottery-like stocks (Kumar (2009)). The influence of gambling behavior in stock markets is likely to increase and could have economically important effects on stock returns. Especially, in market settings that superficially resemble actual gambling environments and in which skewness is a prominent feature, people's gambling attitudes may influence market outcomes (Kumar and Lee (2009)).

There are empirical evidences that gambling motives may influence investment decisions. Kumar (2009) examine whether socio-economic and psychological factors which are known to influence lottery purchases lead to excess investment in lottery-type stocks. Using monthly portfolio holding and trading data from a large U.S. brokerage house, he finds that individual investor invests disproportionately more in stocks with higher idiosyncratic volatility, higher skewness, and lower prices even though these stocks have lower mean returns and they exhibit an aversion for stocks with non-lottery features. In contrast, institutional investors prefer stocks with higher mean returns, lower idiosyncratic volatility, lower skewness, and higher prices. He indicates that people's attitudes toward gambling are reflected in their stock investment choices and stock returns. He further suggests that due to our fundamental desire to gamble, the link between socio-economic dynamics and the stock market behavior may be stronger than currently believed. Rich people's behavior is not different, but their gambles do take a different shape and form. Rich people invest in sophisticated financial instruments that similar allow them to preserve capital and gamble with only a small fraction of their money.

2.5 Gambling in Thailand

In Thailand, gambling, both legal and illegal, is very much a part of the daily life of all levels of Thai society, from the wealthy socialites to the poorest of the trishaw drivers (Klausner (1987)). Gambling appeals to almost everyone from the migrant worker to the stock market executive. All kinds of people are attracted to the numerous of options for betting money. Since gambling is social and interactive, it is understandable that many Thais choose gambling as a favorite pastime. This is not meant that Thais gamble more than citizens of other countries. According to Phongpaichit et al. (1999), the proportion of people who gamble and the amount as a percent of GDP, are about the same in Thailand as in Australia and other countries.

Thailand has a long history of gambling. As reported by Brandy (2003) that dating back to the 10th century, the Chinese bean guessing game is one of the earliest gambling games. British East India documents from 1620 mention gambling as a major vice of Bangkok residents. King Rama III, recognising Thais' love of gambling, allowed legal gambling dens throughout the kingdom to generate tax revenue. By the late 19th century, many people were addicted to gambling, which led to increases in bankruptcy and crime. This influenced King Rama V, to outlaw gambling. In the mid 1940's the government once again experimented with gambling legalization for tax purposes but only members of the wealthy class were to be admitted into the casinos. The Ministers in charge ignored the governmental rule and opened its doors to anyone wishing to chance their luck. Substantial debt slavery and degeneration of social values resulted; causing the government outlawed gambling until today. However, there are still many forms of gambling in Thailand for instance horse-racing, stock-market lottery, betting on boxing, cock-fighting, bull-fighting, Siamese fish-fighting and variety forms of card playing. Currently, only horse racing and government lottery is legal in Thailand.

Globally, lottery gambling involves a large amount of money. According to Ariyabuddhiphongs and Chanchalermporn (2006), the world lottery sales in 2002 were reported the amount of \$132.2 billion. While LaFleur's 2008 World Lottery Almanac reports that the worldwide lottery sales were almost \$224.3 billion in 2007. It increases almost twofold within five years. Lottery participation is also widespread in Thailand. Government lottery draws are announced on the 1st and 16th of every month. Presently, there is 46 million lottery tickets are sold before each drawn. The total of lottery tickets sold for each month is 92 million tickets which exceed the total amount of population in Thailand. In 2000, National Economic and Social Development Board (NESDB) reported that 62.49 percent of Thai people participate in government lottery and 71.82 percent involve in an illegal underground lottery. In 2007, the study of Thai lottery-players' behavior conducted by University of Thai Chamber of Commerce, Assumption University, and Suan Dusit Poll reveals that 42 percent of Thai people buy lottery because they like to gamble, while 29 percent of them buy lottery for a hope to win a large amount of money. On average, government lottery ticket returns about 0.6 Baht to players for a 1 Baht wager (Panitkijkosol (2007)). This relatively large negative expected return does not appear to have reduced Thai individuals participate in lotteries at all.

In 1977, Thais spent about 2,300 million baht on lottery tickets (Klausner (1987)). Astonishingly, the money pay for lottery ticket in 2009 is increasing to be over 2,000 million bath for each drawn or more than 48,000 million baht a year. But a much larger amount of money is involved in the illegal underground lottery or Huay taidin. According to a study by the Thai Farmers Research Center, in 1995, the total amount spent on Huay taidin was around 110 billion baht or 2.5 percent of GNP. The center estimated that seven out of every ten people in the working age group of 15 – 65 played the underground lottery, spending on average one hundred baht per lottery draw. Nevertheless, a study of money spent on the underground lottery in 1995 by Phongpaichit et al. (1999), the estimation is more than three time higher than that made by the Thai Farmer Research

Center. During August 2003 to November 2006, government brought part of the massive underground lottery system into the two- and three-digit lottery scheme. The two- and three-digit lottery or Huay bondin produced approximately 3,100 million baht per each draw, or 74,400 million baht a year, for the Government Lottery Office which was more than that of government lottery could make 1,840 million baht for each draw at that time. Government' revenue had increased over 130,000 million baht form the total of 80 draws of two- and three-digit lottery running.

The popularities of lottery involvement are pervasive in Thailand while the preference of investors for the lottery-like stocks is not well presented in Thai stock market. Our study examines whether the gambling preferences of Thai people carry over into the stock market. According to Green and Hwang (2009), skewness effect is stronger during periods of high investor sentiment. This study also focuses further consideration on gambling seasonality which we conjecture that retail investors reveal time varying emotional action to the stock market along with the lottery-like stock.

2.6 Retail Investor and Behavioral Bias

In his book chapter, Prospect theory in the wild: evidence from the field, Camerer describes ten regularities in naturally occurring data that are anomalies for expected utility theory but can all be explained by three simple elements of prospect theory: loss aversion, reflection effects, and nonlinear weighting of probability. He concludes his chapter that prospect theory is valuable because it can explain ten patterns observed in a wide variety of economic domains with a small number of modeling features. Different features of prospect theory help explain different patterns. Loss aversion can explain the extra return on stocks compared with bond (the equity premium), asymmetries in consumer reactions to price increases and decreases, the insensitivity of consumption to bad news about income, and status quo and endowment effects. Reflection effects can explain disposition effect, insensitivity of consumption to bad income news, and the shift toward longshot betting at the end of a racetrack day. Nonlinear weighting of probabilities can explain the favorite longshot bias in horse-race betting, the popularities of lottery ticket with large jackpots. Shefrin and Statman (1985) point out that because investors dislike incurring losses much more than they like gains and are willing to gamble in the domain of losses, investors will hold on to stocks that have lost value (relative to their purchase price) too long and will be willing to sell stocks that have risen in value. They called this the “disposition effect”. The disposition effect is inconsistent with the expected utility theory because the purchase price of a stock should not matter much for whether investors decided to sell it. If investors think the stock will rise, they should keep it: if they think it will fall, they should sell it. Moreover, tax laws, in the U.S. stock market, promote investors to sell losers rather than winners because such sales generate losses that can be used to reduce the taxes owed on capital gains. Disposition effects have been found in many studies from many market setting, including in Thai stock market.

Odean (1998) obtains data from brokerage house about all the transaction of a large sample of retail investors He find that investors hold losing stocks a median of 124 days and hold winners only 104 days. In his sample, the unsold losers’ return is 5% in the subsequent year, while the winners’ return is 11.6% if they are sold in the later year. Fascinatingly, this winner-loser difference disappears in December. In December, investors have a last chance to incur a tax advantage from selling losers, thus their reluctance to incur losses is temporarily overwhelmed by their reluctance to save on taxes. In the similar vein, Barberis, Huang, and Santos (1999) include the loss-aversion in a standard general equilibrium model of asset pricing. They show that loss-aversion and a strong “house money effect” (an increase in risk-preference after stocks have risen) are both necessary to explain the equity premium.

Kahneman and Tversky (1979) have stressed out that the presence of prior gains and losses raises complicated concerns. They suggested that when there are situation in which gains and losses are coded relative to an expectation or aspiration level that differs for the status quo. In these situations, the outcomes of an act affect the balance in an account that was previously set up by a related act. For example, a person who has not made peace with his losses is likely to accept gambles that would be unacceptable to him otherwise.

Thaler and Johnson (1990) investigated how prior outcomes are combined with the potential payoffs offered by current choices and propose an editing rule to describe how decision makers frame such problems. They present data from real money experiments supporting a “house money effect” (increased risk seeking in the presence of a prior gain) and “break-even effects” (outcomes which offer a chance to break even are especially attractive in the presence of prior losses).

2.7 Investor Behavior and Stock Market Anomaly

The calendar effect have persisted as an area of interest for finance researcher in the last three decades as the presence of this anomaly that has been evidenced in the most developed capital markets. Day-of-the-week, the end of the month, the month of the year are the most prominent of the Calendar effect (Ali and Akbar (2009)). It is appealing to connect investors’ moods as a explanation for the stock market anomaly. Since emotion and mood may have a large role on preferences. In fact, emotions have a greater impact on decisions than cognitive considerations because emotions often overrule our cognition (Faustino, Kaizeler, and Marques (2009)). Barberis and Huang (2008) and Thaler (1985) find that investors have a predisposition towards selecting stocks with lottery features at the turn of the year. These stocks perform well in January but underperform for the remainder of the year. A number of studies show that emotions substantially influence decisions in a way that differs substantially from the rational pattern. For instance, the well known Monday anomalous explanation, Gondhalekar and Mehdian (2003) examine the blue-Monday hypothesis for the period of 1971 to 2000. They find the Monday pattern is widespread across industries tracked by the NASDAQ sub-indices. The findings based on proxies for investor pessimism (discounts on closed-end funds, small stock returns, consumer confidence, and pessimism about buying houses) suggest that for many industries the Monday effect is more pronounced in period of pessimism among investors. Abraham and Ikenberry (1994) also suggest a psychological link arguing that a significant positive correlation of low Monday effects with the return for the previous returns as a proxy for market-wide unfavorable information.

In “A survey of the Monday effect literature”, Pettengill (2003) identifies the possible explanations for Monday effect and states that in the light of the research reported in this volume, a few words of summary and conclusion are appropriate. Of the possible explanations, trading patterns from various traders still appears to be the most promising avenue for inquiry. The most likely source of Monday effect is real economic and behavioral phenomena. For an anomaly so well publicized to have persisted for so long. He concludes that the market is so inefficient it cannot learn from its own history or that the Monday effect comes from a rational response to relevant information. Thus, one challenge that lies ahead is to measure investors’ behavioral responses. Not only had the Monday effect, other irregularities in the stock market also linked to the impact of investors’ moods. There is plenty psychological support that people tend to have a more optimistic valuation of future prospects when they are in a better mood. For example, Arkes, Herren, and Isen (1988) observe that sales of Ohio State lottery tickets increase in the days after a victory by the Ohio State University football team. Saunders (1993) and Chang, Chen, Chou and Lin (2008) suggest that weather has a significant influence on investors’ trading behavior. They find that stock returns are generally lower on cloudier days and argue that weather influences stock returns because it affects investors’ mood.

Hirshleifer and Shumway (2003) confirm the weather effect across international markets. Goetzmann and Zhu (2005) find a strong correlation between stock returns and cloud cover. Cao and Wei (2005) hypothesize that temperature influences stock returns as some psychological researches show that extreme weather changes human behavior. They relate stock returns to temperature changes during the year and find a reverse relationship between temperature and stock returns. They conclude that lower temperatures are associated with higher stock returns due to aggressive risk-taking and higher temperatures can lead to higher or lower stock returns depending on which mood dominates, aggression (risk-taking) or apathy (risk-avoidance).

In Thai stock market, Seangjun (2008) investigates whether there is relationship between investor mood and daily Thai stock returns and trading volume during 1992 and 2006. The paper classifies investor’s mood as (i) emotion variables; holiday and sport event (ii) belief variables; lunar and Friday 13th, (iii) weather variables; rain and cloud. The study finds statistically significant relationship between Thai stock returns, trading volumes and holiday, sport competition results, Friday 13th, and weather but no relationship with lunar. The strongest relationship is the positive effect of preholiday on stock returns and the negative effect of could and preholiday on trading volumes. Moreover, retail investors are more likely to deviate from rational valuation of securities than are institutional investors. The study concludes from psychology viewpoint that good mood induces positive decision making and then over-valuation. Recently, Nirojsil (2009) examines the relationship between weather factors and stock market returns in Thailand during May 1992 to December 2008. Considering that the weather can affect human moods, it would also affect investors' decision making. The results show negative relationship between temperature and stock market returns. He concludes that his study implies that Thai stock market may be inefficient due to the irrationality (temperature effect) in the market.

2.8 Different Gambling Mentality in Different Time Period

The behavioral alternative hypothesis suggests that individual may exhibit different gambling mentality in different period of time. For instance, the typical seasonality in Las Vegas gambling is the period between Superbowl Sunday and the Chinese New Year (Doran, Jiang, and Peterson (2009)). There is also evidence showing that people around the world aggressively participate in a variety form of gambling to celebrate the New Year. For example, Chinese, Greeks, and Turkish usually visit casinos. Doran et al. (2009) analyze whether investor exhibit a New Year's gambling preference and whether gambling preference impact prices, returns and trading volume of assets with lottery features. They evaluate the out-of-the-money call options and lottery-like stocks in US and Chinese market and find that all of these assets have abnormally high prices, returns and trading volumes at the turn of the New Year. They also evidence that in the option markets small investor exhibit strong gambling preferences in the New Year and reveal such preferences through buying call option. Overall evidences support that investor most likely place lottery-type bets in financial markets at the start of a new year. Their empirical findings reveal that such preference is exhibited in the financial markets and has a strong price impact. They wrap up that 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. They conclude that gambling is built-in preference of some individuals and tend to be stronger in the New Year. Furthermore, Benartzi and Thaler (2001) suggest that receiving annual reports and filling taxes at the year-end likely force investors to evaluate and modify their portfolios. Risk taking is likely to build up after their portfolio valuation. New Year can be viewed as an ordinary starting point for a new phase of investing or gambling. Skeel (2007) points out that there are a large numbers of investors betting on uncertain outcomes in much the same way as gamblers who go to casinos or buy lottery tickets. It is possible that the different level of trading during different time period is a partial replacement for entertainment associated with gambling. The gambling motives may influence investment decision differently during different calendar time.

According to Thaler and Johnson (1990), the experimental work on individual decision making finds that individuals have a tendency to engage in risk seeking activities after experiencing outcome payoff in prior round of gambling. Then retail investors may trade more on the day after the game to take their minds off the football game. Since football is the people’s game. It has an extraordinary popularity worldwide: large numbers of people attend live matches and play football, larger number still are television supporters. People care about and passionate about football (Morrow (1999)). Several psychology literatures illustrate that sporting event can effect human behavior; in particular, literature suggests wins are associated with a good mood and losses with a bad mood. The effect of sport results leads to sudden mood changes which can impact a trading decision in the stock market. Edmans et al. (2007) investigate the effect of sports sentiment on stock prices of 39 countries, including Thailand. Using sport outcomes to capture moods changes among investors they find that losses in soccer matches have an economically and statistically significant negative effect on the losing in stock market. They also document a loss effect after international cricket, rugby, and basketball games. On average, the effect is smaller in scale for these other sports than soccer, but still economically and statistically significant. The loss effect is stronger in small stocks, which often are excessively held by individual investors and more strongly affect by sentiment. They find no evidence of a corresponding effect after wins for any of the sports. The asymmetric reaction suggests that the reference point of soccer fans is that their team will win. A greater effect after football losses than after football wins shows the pre-game expectations of how their team will perform. They argue that a mood variable must satisfy three key characteristics to rationalize studying its link with stock returns. First, it must drive mood in a substantial and unambiguous way. Second, it must impact the mood of a large proportion of the population. Third, the effect must be correlated across the majority of individuals a within a country. The international football results satisfy these criteria. International football competitions are the very few events that play at regular intervals and that are recognized by a large amount of fans around the world. For example, the number of television viewers that followed the 2002 World Cup in Korea/Japan was more than 25 billion. They find a significant strong negative stock market reaction to losses by national football teams. This loss effect is stronger in small stocks and in more important games.

Overall, related literatures illustrate that retail investors have preference that diverge from rational investors and are vulnerable to errors in evaluating risk. Several psychology evidences show that individual preference bias have a significant impact on stock market. Linking to the gambling preference framework that the influence of gambling behavior in stock markets is likely to increase and could have significant impact on stock price, the lottery-like stock is prone to be most affected by investor sentiment. Retail investors may exhibit stronger preference toward lottery-like stock relative to the other types of investor. This behavioral supposition further suggests that retail investor may exhibit different gambling mentality in different period of time. Taken together with a plenty psychological supports that individual have tendency to engage in risk seeking activities after experiencing outcome payoff in prior round of gambling and the skewness effect is stronger during periods of high investor sentiment which can impact an investment decision in the stock market, an investigation of investors' gambling behavior and gambling seasonality in Thai stock market is more fascinating.

CHAPTER III
RESEARCH HYPOTHESIS

The inconsistent empirical studies on investor trading behavioral biases suggest the opportunity for the closer investigation to the gambling behavior in the stock market. We explore this behavioral issue along the two main themes. Our testable hypotheses presented in this chapter consist of (i) the investor's gambling trading behavior and (ii) the gambling seasonality in Thai stock market.

3.1. Gambling Preference in Thai Stock Market

Finance literatures evidence that retail investors are particularly exposed to behavioral bias that weakens their ability to make rational investment decisions and this bias is stronger in a situation where firm-specific uncertainty is very high (Coelho and Taffler (2009)). The behavioral bias, i.e. illusion of control, leads people to think that they can predict the future better than they actually can and to act as if they can control random events. This bias leads stock traders to believe that their chosen better stocks. Gambling-motivated hypothesis suggests that investor tends to place high subjective valuations on low probability events, which exhibit gambling preferences with positively skewed payoffs. As documented by many empirical studies, for example, the purchase of insurance and lotteries, portfolio under diversification, and portfolio overweighting on lottery-type stock.

Many finance studies presume that, on average, retail investors are less informed and less professional skill in processing information than institutional and foreign investors. With the important role in managing other people's money, their professional skill, and their full time to monitor the market, the institutional investors are more efficient than retail investors in analyzing the information and they have incentive and volume to make it economical in acquiring expensive information and technology. They can create the better quantitative models from underlying information. This significantly lessens the impact of one person's biases on the investment decision.

Taken together with the irrefutable facts of a widespread gambling preference, lottery participation, and with a feature of lottery-like stocks which are likely to be attractive to many retail investors, we hypothesize that;

Hypothesis 1: Retail investor gambling preference

H_1: Retail investors exhibit higher buying demand level for lottery-like stock than other investors do.

Gambling refers to activity where an individual take a large risks but the reward is not corresponding with the level of risk taken. Gamblers engage in gambling despite the expected returns are negative. They still undertake the bets because they derive utility from the excitement of being in risky situation. In the stock market, if investors have some informational advantage, they should be able to identify the lottery-like stocks with superior performance and generate higher returns from their lottery-like stock trading. In contrast, if their lottery-like stock trading is rooted by gambling-motivated decision, it should have negative impact on their investment. Large bodies of literature shows that retail investors' investment decision are poorer relative to institutional and foreign investors. Their portfolio performances underperform their counterparts' portfolios. (For example, Odean (1999), Barber and Odean (2000), Grinblatt and Keloharju (2000), Hvidkjaer (2006), Froot and Ramadorai (2001), Barber, Odean, and Zhu (2005)) Concerning that gambling-motivated decision can be an alternative explanation for the investment underperformance of retail investor's, our second hypothesis is;

Hypothesis 2: Lottery-like stock portfolio performance

H_2: Lottery-like stock portfolio of retail investors underperforms the lottery-like stock portfolio of other investor types.

3.2. Gambling Seasonality in Thai Stock Market

The behavioral alternative hypothesis suggests that individual may exhibit different gambling mentality in different periods of time. For instance, the typical seasonality in

Las Vegas gambling is the period between Superbowl Sunday and the Chinese New Year (Doran et al. (2009)). Thaler and Johnson (1990) find, in their experimental study, that individuals have a tendency to engage in risk seeking activities after experiencing outcome payoff in prior round of gambling. Moreover, the House money effect suggests that investors become less risk averse following prior gains. While the Break-even effect proposes that after experiencing losses but being offered a chance to breakeven, individuals are also more willing to gamble. According to Green and Hwang (2009) and Doran et al. (2009), gambling is a built-in preference of some investors and tends to be higher during the period of high investor sentiment. Their empirical findings also reveal that such preference is exhibited in the financial markets and has a strong price impact. Barberis and Hwang (2008) argue that the arbitrage mechanism is possible to collapse in an economy occupied with investors that do not match with the traditional mean-variance paradigm but follow the cumulative prospect theory. Retail investors displaying strong gambling preferences are likely candidates to be cumulative prospect investors and their gambling behavior can impact prices in the stock markets.

These inconsistent manners bring us to the third hypothesis that investors gambling demand may have time-variation and their demands can impact stock prices. Hence we breakdown our investigation of investor's trading behaviors in different time periods into three aspects; (i) gambling seasonality and the market anomaly, (ii) gambling seasonality and the calendar effect, and (iii) gambling seasonality and the market sentiment.

The inconclusive empirical studies on investor trading behavior as the Monday and January effect explanation suggest the opportunity to investigate the time-variation in investor gambling demand on Monday (in January). Since the return seasonality in Monday and January is most pronounced among stocks in which retail investors represent a large portion (Pettengill (2003) and Jacobson (2007)). There is also evidence showing that people around the world, such as in Las Vegas, China, Greek, Turkey, aggressively participate in a variety form of gambling to celebrate the New Year. Barberis and Huang (2008) and Thaler (1985) find that investors have a predisposition towards selecting stocks with lottery features at the turn of the year. These stocks perform well in January but underperform for the remainder of the year. The aggressive gambling preference at the beginning of the year can be the root of the January effect. While the Monday anomaly, Pettengill (2003) concludes that trading patterns from various trades still appears to be the most possible explanation for this well-known anomaly. Monday is conjectured to have higher investor sentiment and trading activity of retail investor increases whereas the activity of institutional investor decreases on Mondays relative to other weekdays (Lakonishok and Maberly (1990)). Incorporating investors' gambling behavior into an investigation may give us an insight clarification of the conventional well-known anomalies; January and Monday effect. We hypothesize that

Hypothesis 3a: Gambling seasonality and the market anomaly

H_{3a1}: Relative to institutional and foreign investors, retail investors exhibit higher buying demand for the lottery-like stocks on Monday (in January).

H_{3a2}: The lottery-like stock return outperforms the nonlottery-like stock return on Monday (in January).

Calendar effect have persisted as an area of interest for finance researcher in the last three decades as the presence of this anomaly that has been evidenced in the most developed capital markets. Day-of-the-week, the end of the month, the month of the year are the most prominent of the Calendar effect (Ali and Akbar (2009)). According to Skeel (2007), large numbers of stock market investors are betting on uncertain outcomes in much the same way as gamblers who go to casinos or buy lottery tickets. It is possible that the different level of trading during different time period is a partial replacement for entertainment associated with gambling. The gambling motives may influence investment decision differently during different calendar time. We hypothesize that

Hypothesis 3b: Gambling seasonality and the calendar effect

H_{3b1}: Relative to institutional and foreign investors, retail investors exhibit different buying demand level for the lottery-like stocks on the different day of the week (month of the year).

H_{3b2}: The lottery-like stock return outperforms the nonlottery-like stock on the day (month) that buying demand of lottery-like stocks is higher.

When economics opportunity is not very bright, people find their tiny probability of a large gain more attractive therefore they exhibit stronger preference for lotteries (Kumar (2009). Lottery studies suggest that when economic opportunity is not very bright, people find the small probability of a large gain more attractive and consequently, they exhibit stronger preference for lotteries. Furthermore the prospect theory put forward that investors are more sensitive to stock market losses than to stock market gains; they perceive the stock market to be very risky and charge a high average return as compensation. Concerning the context of stock market condition, we hypothesize that

Hypothesis 3c: Gambling seasonality and the market sentiment

H_{3c1}: Relative to institutional and foreign investors, retail investors exhibit higher buying demand for the lottery-like stocks on the trading day that the market decreases more than 3%.

H_{3c2}: The lottery-like stock return outperforms the nonlottery-like stock return on the trading day that market decrease more than 3%.

CHAPTER IV
DATA AND VAIRABLE CONSTRUCTION

This chapter starts by introducing the data set used in our study, presenting the procedures used to classify the lottery-like stocks and reporting the basic characteristics of lottery-like stocks. The identification of trader-initiated is described in the last section.

4.1 Data Set

We examine investor trading behaviors using all individual stocks traded on the Stock Exchange of Thailand (SET) over the sample period from January 1999 to December 2008. The detail transaction data are obtained from the exclusive database of SET. The detail transaction data includes the date and time of transaction, order type, transaction price, transaction volume, security symbol, deal status, and trader type. This transaction data set provided the unique opportunity to analyze the trading behavior of different investor types. Investors' trading data are broadly classified into four categories; retail investor, institutional investor, foreign investor, and broker-owned portfolio. The other crucial data such as market capitalization, market-to-book value, and market index are drawn from the Thompson Reuters DataStream and the SETSmart database. The macroeconomic monthly data include the unemployment rate, the inflation rate, the yield of ten-year government bond, the yield of three-month Treasury bill, and the one-month Inter-bank rate are obtained from the Bank of Thailand website.

4.2 Lottery-like Stock Classification

Lottery ticket's features are low prices compare to the possible size of the payoff. It has a risky payoffs, negative expected returns, and small probability of a very high return. Similar to lottery ticket, lottery-like stocks are identified as the low-priced stocks with high volatility and high skewness. We employ the approach of Kumar (2009) to identify lottery-like stocks and nonlottery-like stocks. The three characteristics of stock are considered to identify the lottery-like stocks; stock price, idiosyncratic volatility, and idiosyncratic skewness. Initially, to identify the lottery-like stocks, stocks are ranked by price at the end of the month *t-1*. The stocks in the lowest 50^{th} percentile are the candidates to be the lottery-like stocks.

At the end of month *t*, the idiosyncratic volatility and idiosyncratic skewness measures using the previous 6 months of daily returns data are computed. The idiosyncratic volatility *(Ivol)* measure is the variance of residual obtained by fitting a four-factor model to daily stock return time-series, where the four factors include three-factors of Fama and French (1993) and a momentum factor. As used in the Carhart (1997), the four-factor model is given as follow;

$$R_{i,t} - R_{f,t} = \alpha_0 + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 WML_t + \varepsilon_{i,t} \qquad (1)$$

where

$R_{i,t}$	:	the daily return of stock *i*
$R_{f,t}$	:	the risk-free rate, Thailand's one-month Inter-bank rate
$RMRF_t$	:	the market return in excess of the Thailand's one-month Inter-bank rate
SMB_t	:	the difference between the monthly return of a portfolio of small stocks and the monthly return of portfolio of big stocks
HML_t	:	the difference between the monthly return of portfolio of high Book to Market (Value) stocks and the monthly return of portfolio of low Book to Market (Growth) stocks
WML_t	:	the difference between the monthly return of portfolio of high return (Winner) stocks during month *t-12* to *t-2* and the monthly return of portfolio of low return stocks (Loser) during month *t-12* to *t-2*.
$\varepsilon_{i,t}$	:	a mean-zero error term

Following Fama and French (1993) and instruction in the Ken French's website, stocks with negative book-to-equity are excluded since in practice, it is complicated to distinguish whether such stocks possess value or growth attributes. We construct the equally weighted portfolios by ranking the sample stocks based on size (market capitalization) and book-to-market ratios for previous 6 months prior to portfolio formation (i.e., month *t-6* to *t-1*). The top 50% based on sizes are referred as big (B) stock portfolio and the remaining stocks are included into the small (S) stock portfolio. The top 30% based on the book-to-market ratios are referred as high (H) book-to-market stock portfolio, the middle 40% and the bottom 30% are referred as medium (M) and low (L) book-to-market stock portfolio, respectively. Then the six intersecting portfolios are formed as SH, SM, SL, BH, BM, and BL. The SMB is the average return on the three small portfolios minus the average return on the three big portfolios [1/3 (SH + SM + SL) – 1/3 (BH + BM + BL)] and the HML is the average return on the two value portfolios minus the average return on the two growth portfolios [1/2 (SH + BH) – 1/2 (SL + BL)]. The momentum factor, WML, is constructed using prior (2-12) month returns. The WML is the average return on the two winner (W) or high prior return stock portfolios minus the average return on the two loser (L) or lower prior return stock portfolios [1/2 (SW + BW) – 1/2 (SL + BL)]. The idiosyncratic volatility is obtained as the variance of the residual taken form fitting a four-factor model to the daily stock return.

To measure idiosyncratic skewness *(Iskew)*, the third moment of residual is obtained by fitting a two-factor model to the daily stock returns time series. The return residuals are estimated from the regressions of daily stock returns on the excess daily market returns and the squared excess daily market return (Harvey and Siddique (2000), Kumar (2009)). In particular, the following regression is estimated;

$$R_{i,t} - R_{f,t} = \alpha_0 + \beta_1 RMRF_t + \beta_2 RMRF_t^2 + \varepsilon_{i,t} \tag{2}$$

where

$R_{i,t}$: the daily return of stock *i*

$R_{f,t}$: the risk-free rate, Thailand's one-month Inter-bank rate

$RMRF_t$: the daily market return in excess of the risk-free rate

$RMRF_t^2$: the squared of daily market return in excess of the risk-free rate

$\varepsilon_{i,t}$: a mean-zero error term

Then, all stocks in the sample are sorted into quintiles along these three characteristics. Within the set of low-priced stocks, the highest idiosyncratic skewness is used as the second defining characteristic of lottery-like stocks. As a final point, within the set of stocks that have low prices and high idiosyncratic skewness, stocks with higher idiosyncratic volatility are classified as the lottery-like stocks. In contrast, the high price stocks with low idiosyncratic skewness and low idiosyncratic volatility are classified as the nonlottery-like stock. The remaining stocks are categorized as the other stocks. The classification process of the lottery-like stock is repeated for every six months, in consequence our set of the lottery-like stocks are changed every six months. During our sample period of 2,451 days, there are 76,488 stock-days of the lottery-like stocks (15.78%), 71,878 stock-days of the nonlottery-like stocks (14.38%), and 336,262 stock-days of the other stocks (69.39%).

Table I Panel A presents the mean monthly basic characteristics of lottery-like stocks, along with those of nonlottery-like stocks and other stocks. There are 963 stock-months of lottery-like stocks, 961 stock-months of nonlottery-like stocks and 4,397 stock-months of other stocks during our ten-year sample period. Similar to those of Kumar (2009), relative to nonlottery-like stocks, the lottery-like stocks, on average, have lower market capitalization (4,791 million baht), lower liquidity, and lower price. The average monthly return of lottery-like stock price is 0.713% while the nonlottery-like stock monthly return is 0.925%. The lottery-like stocks represent 4.01% of the total stock market capitalization but in terms of their total number, they represent 15.23% of the market while nonlottery-like stocks represent 25.98% of the total stock market capitalization and 15.20% in terms of their total number. Additionally, they have a higher volatility, higher skewness, and more sensitive to the Fama French's and the momentum factors. Descriptive statistics of daily return are reported in Panel B. Obviously, lottery-like stock has lower daily return, higher volatility, and higher skewness relative to their counterparts. Interestingly, the other stocks have features in between lottery-like and nonlottery-like stocks. Initially we can observe that the lottery-like stocks can be perceived as the risky payoff choice of a cheap way of buying a tiny probability of a very high return. In the other words, lottery-like stocks are apparent as the gambling device in the stock market.

4.3 Buyer- and Seller-Initiated Trade Identifications

This study employs the trader-initiated trades throughout the analysis. According to Lee and Ready (1991), the initiated trades aim to capture the trade pressure exerted by investors. They exploit the fact that most trades take place when one side of the transaction demands immediate execution. The buyer-initiated trades indicate buy pressure and the seller-initiated trades indicate sell pressure. Since the initiation makes the trade possible, this trade usually recognized as the price setting trade.

The classification of trades as buyer-initiated or seller-initiated is done by observing the deal time and order submission time. Since SET transactional database provides us the data on the order file and deal file. In the order file, data include all of the historical transactional limit buy order, limit sell order, market buy order and market sell order in term of order prices, order volume and order value for all stocks. It also provides the order submission date and time, type of trades submitting the order, type of orders, trading board type, order status, and quantity of the orders matched and remaining quantity. In the deal file, data include the historical transactional buyer-initiated and seller initiated trades in terms of executed price, trade size and trade value for all stocks. The deal file also provides trading date and time, deal confirmation number, buy order and sell order time, and buy order and sell order number. In order to classify the buyer-initiated or seller-initiated, the deal time and order submission time are observed. Buyer-initiated trades are those trades in which deal price occur at the best quoted ask whereas seller-initiated trades are those trades in which deal price occur at the best quoted bid. The deal file represents all the trades occurred at the best bid and best ask. It provides us with buy-order and sell-order submission time.

Given the deal time and order submission time, we can match the buy-order submission time and sell-order submission time for each transaction. Therefore, we can define the buyer-initiated trades as the trades in which the buy order time takes place after the sell order time. The seller-initiated trade as the trades in which the sell order time take place after the buy order time.

CHAPTER V
RESEARCH METHODOLOGY

We begin this chapter by describing the procedures used to test the investor's gambling preferences on the lottery-like stocks and then discuss the models employed to analyze the gambling seasonality during the different periods of time.

5.1 Gambling Preference in Thai Stock Market

In this section, we discuss several measures and methodologies used to analyze investors' trading behavior. Following Goetzman and Zhu (2005); Trading Volume, Net Buy, and Buy-Sell Imbalance are used as investor trading behavior measures. Throughout the study, we employ investor-initiated trades to investigate trade pressure of investors. According to Lee and Ready (1991), the initiated trades aim to capture trade pressure exerted by investors. The buyer-initiated trades indicate buy pressure and the seller-initiated trades indicate sell pressure. Since the initiation make trade possible, this trade usually recognized as the price setting trade.

5.1.1 Investor Trading Activity

To test our first hypothesis, daily trading activity of different investor types is regressed on *DummyStockType*, a dummy variable for lottery-like and nonlottery-like stocks. The stock price variable is included as the control variable to capture the effect of prices on the investor's trading activities. The market return and trading volume variables are included to capture the effect of market and the lagged of trading activity variable also included to control for a possible auto-correlation. The following regression is utilized;

$$\begin{aligned} ln(Total\ trading\ activity)_{j,t} = \ & \beta_0 + \beta_1 DummyLot_{j,t} + \beta_2 DummyNonLot_{j,t} \\ & + \beta_3 StockPrice_{j,t} + \beta_4 MktRet_{j,t} + \beta_5 MktRet_{j,t-1} \\ & + \beta_6 ln(SETVol)_{j,t} + \beta_7 ln(SETVol)_{j,t-1} \\ & + \beta_8 ln(Total\ trading\ activity)_{j,t-1} + \varepsilon_{j,t} \qquad (3) \end{aligned}$$

where

Total trading activity$_{j,t}$	:	total initiated-trading volume (value) by investor *j* on day *t*
Total trading volume$_{j,t}$	:	total buy-initiated volume plus total sell-initiated volume by investor *j* on day *t*
Total trading value$_{j,t}$	:	total buy-initiated value plus total buy-initiated value by investor *j* on day *t*
DummyLot$_{j,t}$	:	dummy variable set equal to one for lottery-like stocks and equal zero otherwise
DummyNonLot$_{j,t}$	:	dummy variable set equal to one for nonlottery-like stocks and equal zero otherwise
StockPrice$_{j,t}$	:	the price of stock *i* on day *t*
MktRet$_{j,t}$	:	the stock market return on day *t*
MktRet$_{j,t-1}$	:	the stock market return on day *t-1*
SETVol$_{j,t}$	:	the market trading volume on day *t*
SETVol$_{j,t-1}$	:	the market trading volume on day *t-1*
Total trading activity$_{j,t-1}$	:	Total initiated-trading volume (value) by investor *j* on day *t-1*
$\varepsilon_{j,t}$	:	a mean-zero error term

To improve the efficiency of parameter estimation, the White Heteroskedasticity Consistent Estimator for standard errors is employed. We expect β_1 of retail investor to be significantly positive and higher than β_1 of other investor types.

5.1.2 Investor Trading Imbalance

To further examine whether investors' buy or sell decision is responsive to the lottery-like stock's and whether there is a difference trading pattern among different group of investors. The Buy-Sell imbalance (*BSI*) measure is used. BSI is widely used in the recent behavioral finance literature as a proxy for difference of opinions of different investors (for example, Barber and Odean (2001), Choe, Kho, and Stulz (2005), Goetzman and Zhu (2005), Venezia and Shapira (2005), Barber, Odean, and Zhu (2006), Henker and Henker

(2007), Kumar and Lee (2009)). In particular, for each of investor types, we calculate the BSI as

$$BSI_{jit} = \frac{(Buy_{jit} - Sell_{jit})}{(Buy_{jit} + Sell_{jit})} \qquad (4)$$

where

BSI_{jit}	:	Buy – Sell imbalance of stock *i* by investor *j* on day *t*
Buy_{jit}	:	buy-initiated volumes (value) of stock *i* by investor *j* on day *t*
$Sell_{jit}$	:	sell-initiated volumes (value) of stock *i* by investor *j* on day *t*

The BSI results in a variable that ranges between -1 and 1, indicating the direction of trading while eliminating the confounding effects of different trading volumes. In particular, BSI indicates whether investors are net buyers (BSI > 0, a positive change in investor's stock sentiment) or net sellers (BSI < 0, a negative change in investor's stock sentiment). In other words, BSI measure is a directional indicator of net investor demand for that stock (Barber and Odean (2002)). For further examination, the *BSI* of each investor types is used as dependent variable in the following time-series regression model;

$$\begin{aligned} BSI_{j,t} = {} & \beta_0 + \beta_1 DummyLot_{j,t} + \beta_2 DummyNonLot_{j,t} \\ & + \beta_3 StockPrice_{j,t} + \beta_4 MktRet_{j,t} + \beta_5 MktRet_{j,t-1} \\ & + \beta_6 \ln(SETVol)_{j,t} + \beta_7 \ln(SETVol)_{j,t-1} \\ & + \beta_8 BSI_{j,t-1} + \varepsilon_{j,t} \end{aligned} \qquad (5)$$

where

$BSI_{j,t}$	:	Buy-Sell imbalance of investor *j* on day *t*
$DummyLot_{j,t}$	:	dummy variable set equal to one for lottery-like stocks and equal zero otherwise
$DummyNonLot_{j,t}$	:	dummy variable set equal to one for nonlottery-like stocks and equal zero otherwise
$StockPrice_{j,t}$	:	the price of stock *i* on day *t*
$MktRet_{j,t}$	:	the stock market return on day *t*

$MktRet_{j,t-1}$	:	the stock market return on day t-1
$SETVol_{j,t}$	:	the market trading volume on day t
$SETVol_{j,t-1}$	:	the market trading volume on day t-1
$BSI_{j,t-1}$	:	Buy-Sell imbalance of investor j on day t-1
$\varepsilon_{j,t}$	:	a mean-zero error term

The stock price variable is included as the control variable to capture the effect of prices on the investor's trading activities. The market return and market trading volume variables are incorporated into the BSI regression as the control variables to capture the effect of market return and market trading volume and the lagged of trading activity variable also included to control for a possible auto-correlation in trading activity. We expect to observe the positive and significant β_1 for BSI of the retail investor. To improve the efficiency of parameter estimation, the White Heteroskedasticity Consistent Estimator for standard errors is employed.

5.1.3 Investor Sentiment and Macro-economic Conditions

The popularity of lottery-playing and gambling increased dramatically during bad economic times (Brenner and Brenner (1990). To further examine whether different investor types have different sensitivity to macro-economic condition and whether investor propensity to invest in the lottery-like stock is analogous to the demand in lottery ticket during economic depression, the following time-series regression model is employed to estimate the influence of macro-economic conditions on investors' tendency to demand more of lottery-like stocks.

$$\begin{aligned} EBSI_t = \beta_0 & + \beta_1\, UnEmploy_{t-1} + \beta_2\, UnExpInf_{t-1} + \beta_3\, TS_{t-1} + \beta_4\, MPI_{t-1} \\ & + \beta_5\, MktRet_t + \beta_6\, MktRet_{t-1} \\ & + \beta_7\, LotRet_t + \beta_8\, LotRet_{t-1} \\ & + \beta_9\, EBSI_{t-1} + \varepsilon_t \qquad (6) \end{aligned}$$

where

$EBSI_t$	:	the excess Buy-Sell imbalance on month t

$EBSI_t = LBSI_t - NBSI_t$

$LBSI_t$	:	the buy-sell imbalance of a portfolio of lottery-like stocks on month *t*
$NBSI_t$	:	the buy-sell imbalance of a portfolio of the other remaining stocks on month *t*
$UnEmploy_{t-1}$	:	the unemployment rate on month *t-1*
$UnExpInf_{t-1}$	:	the unexpected inflation on month *t-1*, the average of the 12 most recent inflation realizations is used to estimate the expected level of inflation
TS_{t-1}	:	the term spread on month *t-1*, the term spread measured as the difference between the yield of a ten-year Government bond and the yield of a three-month Treasury bill
MPI_{t-1}	:	the monthly growth in industrial (manufacturing) production on month *t-1*
$MktRet_t$	:	the mean monthly market return on month *t*
$MktRet_{t-1}$	:	the mean monthly market return on month *t-1*
$LotRet_t$	:	the mean monthly return of lottery-like stocks on month *t*
$LotRet_{t-1}$	:	the mean monthly return of lottery-like stocks on month *t-1*
$\varepsilon_{j,t}$	:	a mean-zero error term

In this regression model, the dependent variable, $EBSI_t$, is the excess buy-sell imbalance for the lottery-like stocks in month *t*. According to Kumar (2009), the $EBSI_t$ is used to measure the excess change in the sentiment of investors which captures the change in investors' bullishness toward lottery-like stocks relative to change in their bullishness toward other remaining stocks. Presumably, different stocks behave differently during different economic cycles, $UnEmploy_{t-1}$ and $UnExpInft_{-1}$ variables proxies for economic conditions are included. MPI_{t-1} attempts to measure the growth rate of economy. Apparently, different stocks will have different exposures to different stages in the business cycle as measured by the growth in manufacturing production. TS_{t-1} is a proxy for measuring expected changes in the future state of economy according to bond market participates. It also may be a proxy for time a risk premia. To detect the effects of returns on investors trading, the market returns and the lottery-like stock returns and its lagged variables are also incorporated as independent variables. The lagged $EBSI_t$ is included to control for a potential auto-correlation in sentiment shifts. We expect β_1, β_2, β_3, and β_4 of retail investors to be significantly negative to confirm that their preference for the lottery-like stock is similar to those of the lottery ticket which is greater during bad economic times.

5.1.4 Lottery-like Stock Portfolio Performance

To test our second hypothesis that gambling-motivated decision can adversely influence investor's portfolio performance. Firstly, we evaluate the performance of the lottery-like and nonlottery-like stock portfolio using a four-factor model used in Carhart (1997) and the CAPM model. The risk-adjusted performance differentials between the lottery-like stock portfolio and the nonlottery-like stock portfolio are calculated and compared. Given the high degree of skewness affecting the distribution of lottery-like stock, we employ equally weighted portfolio (Coelho et al. (2009)). For both model, the average equally weighted portfolio returns of each stock-type are calculated for each month. The hedge portfolio is formed by long the lottery-like stock portfolio and shorts the nonlottery–like stock portfolio. For comparison, the hedge portfolio by long the lottery-like stock and short the other stocks is also calculated. The Carhart (1997) is the three-factor Fama-French model which includes the momentum factor. The four-factor model is given by;

$$R_{p,t} - R_{f,t} = \alpha_0 + \beta_{1p}RMRF_t + \beta_{2p}SMB_t + \beta_{3p}HML_t + \beta_{4p}WML_t + \varepsilon_{p,t} \qquad (7)$$

where

$R_{p,t}$	:	the monthly rate of return of portfolio p
$R_{f,t}$	:	the risk-free rate, Thailand's one-month Inter-bank rate
$RMRF_t$	:	the market return in excess of the Thailand's one-month Inter-bank rate
SMB_t	:	the difference between the monthly return of a portfolio of small (S) stocks and the monthly return of portfolio of large (B) stocks

HML_t : the difference between the monthly return of portfolio of high Book to Market (H) stocks and the monthly return of portfolio of low Book to Market (L) stocks

WML_t : the difference between the monthly return of portfolio of high return (Winner) stocks during month *t-12* to *t-2* and the monthly return of portfolio of low return (Loser) stocks during month *t-12* to *t-2.*

$\varepsilon_{p,t}$: a mean-zero error term

Following Fama and French (1993) and instruction in the Ken French's website, stocks with negative book-to-equity are excluded since in practice, it is complicated to distinguish whether such stocks possess value or growth attributes. We construct the equally weighted portfolios by ranking the sample stocks based on size (market capitalization) and book-to-market ratios for previous months prior to portfolio formation. The top 50% based on sizes are referred as big (B) stock portfolio and the remaining stocks are included into the small (S) stock portfolio. The top 30% based on the book-to-market ratios are referred as high (H) book-to-market stock portfolio, the middle 40% and the bottom 30% are referred as medium (M) and low (L) book-to-market stock portfolio respectively. Then the six intersecting portfolios are formed as SH, SM, SL, BH, BM, and BL. The SMB is the average return on the three small portfolios minus the average return on the three big portfolios [1/3 (SH + SM + SL) – 1/3 (BH + BM + BL)] and the HML is the average return on the two value portfolios minus the average return on the two growth portfolios [1/2 (SH + BH) – 1/2 (SL + BL)].

The momentum factor, WML, is constructed using prior (2-12) month returns. The WML is the average return on the two winners (W) or high prior return stock portfolios minus the average return on the two losers (L) or lower prior return stock portfolios [1/2 (SW + BW) – 1/2 (SL + BL)]. We then examine the risk-adjusted performance of the lottery-like and the nonlottery-like stock portfolios from their alphas. To confirm our prediction, we expect the α_0 of the lottery-like stock portfolio to be significantly lower than the α_0 of the nonlottery-like stock portfolio. Secondly, the CAPM model also employed to investigate the consequence of investors' gambling preferences on portfolio performance;

$$R_{p,t} - R_{f,t} = \alpha_0 + \beta_{1p} RMRF_t + \varepsilon_{p,t} \qquad (8)$$

where

$R_{p,t}$	:	the monthly rate of return of portfolio *p*
$R_{f,t}$	:	the risk-free rate, Thailand's one-month Inter-bank rate
$RMRF_t$	:	the monthly market return in excess of the Thailand's one-month Inter-bank rate
$\varepsilon_{p,t}$	:	a mean-zero error term

To verify the negative impact of gambling-motivated trade, the α_0 of the lottery-like stock portfolio is expected to be lower than the α_0 of the nonlottery-like stock portfolio. Thirdly, in order to observe whether gambling-motivated trading can be an alternative explanation to retail investors' underperformance, we further compare the lottery-like and nonlottery-like stocks portfolio performances across different investor types.

5.2 Gambling Seasonality in Thai Stock Market

This section starts with presenting our regression models used to examine gambling seasonality and the investors' trading behavior. Then the GJR-GARCH model and the bivariate-autoregresssion (VAR) model are discussed.

5.2.1 Gambling Seasonality and Investor Behavior

To investigation whether investors exhibit different gambling mentality in different period of time, we breakdown our investigation of investor's trading behaviors in different time periods into three aspects; (i) gambling seasonality and the market anomaly, (ii) gambling seasonality and the calendar effect, and (iii) gambling seasonality and the market sentiment.

For the hypothesis 3a, as the return seasonality in Monday and January is most pronounced among stocks in which retail investors represent a large portion and Monday is conjectured to have higher investor sentiment and trading activity of retail investor increases whereas the activity of institutional investor decreases on Mondays relative to other weekdays (Lakonishok and Maberly (1990)) while January appeal to be the starting point for the new round of gambling. Barberis and Huang (2008) and Thaler (1985) find that investors have a predisposition towards selecting stocks with lottery features at the turn of the year. These stocks perform well in January but underperform for the remainder of the year.

The gambling preference can be the root of the Monday effect and January effect. We exploit the following regressions to examine our hypothesis 3_{a1};

$$\begin{aligned} ln(Total\ trading\ volume)_{j,t} = {} & \beta_0 + \beta_1 DummyMon\ (Jan)*DummyStockType_{j,t} \\ & + \beta_2 DummyStockType_{j,t} \\ & + \beta_3 StockPrice_{j,t} + \beta_4 MktRet_{j,t} + \beta_5 MktRet_{j,t-1} \\ & + \beta_6 ln(SETVol)_{j,t} + \beta_7 ln(SETVol)_{j,t-1} \\ & + \beta_8 ln(Total\ trading\ volume)_{j,t-1} + \varepsilon_{j,t} \qquad (9) \end{aligned}$$

and

$$\begin{aligned} BSI_{j,t} = {} & \beta_0 + \beta_1 DummyMon(Jan)*DummyStockType_{j,t} \\ & + \beta_2 DummyStockType_{j,t} \\ & + \beta_3 StockPrice_{j,t} + \beta_4 MktRet_{j,t} + \beta_5 MktRet_{j,t-1} \\ & + \beta_6 ln(SETVol)_{j,t} + \beta_7 ln(SETVol)_{j,t-1} \\ & + \beta_8 BSI_{j,t-1} + \varepsilon_{j,t} \qquad (10) \end{aligned}$$

where

For the Monday effect analysis;

DummyMon : dummy variable set equal to one for Monday and equal zero otherwise

For the January effect analysis;

DummyJan : dummy variable set equal to one for January and equal zero otherwise

For our hypothesis 3_{b1}, the gambling motives may influence investment decision differently during different calendar time. We incorporate the *DummySeasonality* of different day of week and different month of the year into the following trading regressions in order to observe whether gambling preference can explain the Day-of-the-Week effect and the Month-of-the -Year effect.

$$\begin{aligned} ln(Total\ trading\ volume)_{j,t} = {} & \beta_0 + \beta_1\, DummySeasonality{*}DummyStockType_{j,t} \\ & + \beta_2\, DummyStockType_{j,t} \\ & + \beta_3\, StockPrice_{j,t} + \beta_4\, MktRet_{j,t} + \beta_5\, MktRet_{j,t-1} \\ & + \beta_6\, ln(SETVol)_{j,t} + \beta_7\, ln(SETVol)_{j,t-1} \\ & + \beta_8\, ln(Total\ trading\ volume)_{j,t-1} + \varepsilon_{j,t} \qquad (11) \end{aligned}$$

and

$$\begin{aligned} BSI_{j,t} = {} & \beta_0 + \beta_1\, DummySeasonality{*}DummyStockType_{j,t} \\ & + \beta_2\, DummyStockType_{j,t} \\ & + \beta_3\, StockPrice_{j,t} + \beta_4\, MktRet_{j,t} + \beta_5\, MktRet_{j,t-1} \\ & + \beta_6\, ln(SETVol)_{j,t} + \beta_7\, ln(SETVol)_{j,t-1} \\ & + \beta_8\, BSI_{j,t-1} + \varepsilon_{j,t} \qquad (12) \end{aligned}$$

where

For the Day-of-the-Week analysis;

DummySeasonality : dummy variable set equal to one for each the day of week (Monday, Tuesday, Wednesday, and so on) and equal zero otherwise

For the Month-of-the-Year analysis;

DummySeasonality : dummy variable set equal to one for each the month of year (January, February, March, and so on) and equal zero otherwise

For our hypothesis 3_{c1}, if investors are more sensitive to stock market losses than to market gains and find their tiny probability of a large gain more attractive, their demand for lottery-like stocks may increase after the extreme market loss. On trading day that the SET index increased or decreased more than 3%, we consider that trading day as the market extremely moves day. For comparison, we also investigate investor demand for lottery-like stock on the trading day the Market increases more than 3%. During our sample period, there are 69 days that market extremely increased and 73 days that market extremely decreased. We also consider the 2% increases (decreases) as the cutting point. There are 198 (192) trading days that the Market increases (decreases) more than 2%.

$$\begin{aligned} \mathit{ln(Total\ trading\ volume)}_{j,t} = \; & \beta_0 + \beta_1 \mathit{DummyMarketMove*DummyStockType}_{j,t} \\ & + \beta_2 \mathit{DummyStockType}_{j,t} \\ & + \beta_3 \mathit{StockPrice}_{j,t} + \beta_4 \mathit{MktRet}_{j,t} + \beta_5 \mathit{MktRet}_{j,t-1} \\ & + \beta_6 \mathit{ln(SETVol)}_{j,t} + \beta_7 \mathit{ln(SETVol)}_{j,t-1} \\ & + \beta_8 \mathit{ln(Total\ trading\ volume)}_{j,t-1} + \varepsilon_{j,t} \qquad (13) \end{aligned}$$

and

$$\begin{aligned} \mathit{BSI}_{j,t} = \; & \beta_0 + \beta_1 \mathit{DummyMarketMove*DummyStockType}_{j,t} \\ & + \beta_2 \mathit{DummyStockType}_{j,t} \\ & + \beta_3 \mathit{StockPrice}_{j,t} + \beta_4 \mathit{MktRet}_{j,t} + \beta_5 \mathit{MktRet}_{j,t-1} \\ & + \beta_6 \mathit{ln(SETVol)}_{j,t} + \beta_7 \mathit{ln(SETVol)}_{j,t-1} \\ & + \beta_8 \mathit{BSI}_{j,t-1} + \varepsilon_{j,t} \qquad (14) \end{aligned}$$

where

DummyMarketMove : dummy variable set equal to one for the trading day that the market increases (decreases) more than 3% and equal zero otherwise

For our hypotheses $H3_{a1}$, $H3_{b1}$, and $H3_{c1}$ we expect to observe the retail investor's β_1 is positive and significant. We also expect the higher β_1 of retail investors, relative to the other types of investor. In order to improve the efficiency of parameter estimation, the White Heteroskedasticity Consistent Estimator for standard errors is employed.

5.2.2 Gambling Seasonality and Stock Return

If the gambling preferences of individual investors do not cancel out, it may influence lottery-like stock returns. There are numerous evidences from gambling and individual risk taking show that investors may exhibit different gambling mentality in different period of time. Accordingly, some time periods may be riskier than others, the expected value of the magnitude of error terms at the high investor sentiment may be greater than at others (Engle (2001)). To deal with this volatility clustering issue, the Generalized Autoregressive Conditionally Heteroscedastic (GARCH) model introduced by Glosten, Jaganathan, and Runkle (1993), or the GJR-GARCH, is used to test our hypotheses; $H3_{a2}$, $H3_{b2}$, and $H3_{c2}$.

The GJR-GARCH model is constructed to capture the potential asymmetric impact of shock on return volatility. The notion that economic shocks have an asymmetric effect on stock markets can be found in arguments suggesting that good news and bad news impact volatility differently. Since it is commonly believed that negative impact shocks generate larger volatility than positive shocks, the GJR-GARCH model implies two regimes for the coefficient of the lagged squared innovation, $\varepsilon_{i,t-1}^2$, depending on the sign of conditional error term. The impact of $\varepsilon_{i,t-1}^2$ on the conditional variance is smaller when positive shock occurs relative to negative shock's impact.

$$R_{i,t} = \alpha_0 + \sum_{j=1}^{k} \phi_j R_{i,t-j} + \alpha_1 DummySeasonalVariable_{i,t} + \varepsilon_{i,t}, \tag{15}$$

$$\varepsilon_{i,t} | \Omega_{i,t-1} \approx N(0, h_{i,t}), \tag{16}$$

$$h_{i,t} = \omega + \delta \varepsilon_{i,t-1}^2 + \gamma \varepsilon_{i,t-1}^2 D_{i,t-1} + \theta h_{i,t-1} \tag{17}$$

where

$R_{i,t}$: the stock *i* daily return on day *t*

$R_{i,t-j}$: the stock *i* daily return on day *t-j*

$DummySeasonalVariable_{i,t}$: a dummy variable is set equal to one for the seasonality of interest and equal zero otherwise; The seasonality of interest are Monday, January, different day-of-the-week, different month of the year, trading day that the market increases (decreases) more than 3%, and trading day after the famous football game.

$\Omega_{i,t-1}$: the information set on day *t-1*

$D_{i,t-1}$: a dummy variable, where $D_{i,t-1}$ equal to one if $\varepsilon_{i,t-1}$ is less than zero, and $D_{i,t-1}$ equals zero otherwise.

In the GJR-GARCH process, δ can be viewed as the "news" coefficient, with higher values implying that more recent news has a greater impact on stock returns and θ reflect the impact of the past variance on stock return, while $\theta + \delta$ measures the persistence of volatility. The GJR-GARCH model allows good news ($\varepsilon_{t-1} > 0$) and bad news ($\varepsilon_{t-1} < 0$) to have different impacts on the conditional variance. The good news has only a δ impact on volatility, whereas bad news has a $\delta + \gamma$ impact on volatility. Therefore, if γ is significant, an asymmetric effect will be detected.

Along with the lottery-like stock features, α_1 of the lottery-like stock is expected to significantly positive and higher than α_1 of the nonlottery-like stock on the time period that gambling demand of investors is higher. While in the time period of lower gambling demand from investors, α_1 of the lottery-like stock is expected to significantly negative and lower than α_1 of the nonlottery-like stock

From all the tests performed in this chapter; we expect to observe that retail investors exhibit the higher preference for the lottery-like stocks relative to other investor types and their investment decision is driven by gambling motive. Furthermore, we also anticipate identifying the time-variation in gambling behavior of different investor types and their sentiments perhaps influence the lottery-like stock returns.

5.2.3 Investor Sentiment and Lottery-like Stock Return Lead-Lag Relation

Given that, by definition, the lottery-like stocks have high idiosyncratic volatility, the arbitrage costs are likely to be high for lottery-like stocks. The idiosyncratic volatility can be used as a proxy for an arbitrage cost (Wurgler and Zhuravskaya (2002)). The investor sentiment may influence the lottery-like stock returns. To evaluate whether the investors' trades are influenced by instant lottery-like stock return and whether their immediate trading behavior could influence lottery-like stock returns. Following Froot, O'Connell, and Seasholes (2001), the bivariate vector-autoregression (VAR) framework is used to determine the relation between investors' sentiment and lottery-like stock returns. The dependent variables is the lottery-like stock return on day t ($LotR_{j,t}$) and the Buy-Sell imbalance ($BSI_{j,t}$) variables is used to measure the sentiment of investors in the corresponding day t. The regressors are the set of lagged dependent variables of both equations while the numbers of proper lags are justified by using Akaike and Schwartz criterions.

$$BSI_{j,t} = \beta_0 + \beta_1 \sum LotR_{j,t-i} + \beta_2 \sum BSI_{j,t-i} + \delta_{j,t} \tag{18}$$

$$LotR_{j,t} = \alpha_0 + \alpha_1 \sum LotR_{j,t-i} + \alpha_2 \sum BSI_{j,t-i} + \varepsilon_{j,t} \tag{19}$$

where

$LotRet_{j,t}$	:	lottery-like stock return on day t
$LotRet_{j,t-i}$	:	lottery-like stock return on day $t-i$
$BSI_{j,t}$	:	Buy-Sell imbalance of investor j on day t
$BSI_{j,t-i}$	:	Buy-Sell imbalance of investor j on day t

The Granger-causality tests are also performed to confirm whether prior investor sentiment Granger-causes the lottery-like stock return in the current period, and whether current lottery-like stock return Granger-causes investor sentiment in the following period. A statistically significant two-way causality would indicate the existence of a dynamic relation between investor sentiment and the lottery-like stock returns.

From the VAR model and the Granger-causality tests, we anticipate observing the sentiment-return dynamic relation. If the investor sentiment has ability to predict the lottery-like stock return, α_2 is expected to be significantly positive. The β_1 of retail investor is also expected to be significantly positive and higher than β_1 of the other investor types.

CHAPTER VI
EMPIRICAL FINDINGS

The empirical findings are presented in this chapter. We begin by reporting the results of our tests relating to investor gambling preference in Section 6.1 and presenting the findings of time variation and gambling seasonality in Section 6.2

6.1 Gambling Preference in Thai Stock Market

This section presents the results from testing our hypotheses 1 and 2, specifically we show (i) whether retail investors show stronger preference of lottery-like stock than institutional and foreign investors, (ii) whether their propensity to invest in lottery-like stock is corresponding to the demand in the lottery tickets, and (iii) whether their gambling-motivated trading decision is negatively affect their investment performance.

6.1.1. Investor Trading Behavior and Lottery-like Stock

We employed several measures to analysis the first hypothesis that retail investors exhibit stronger preference for lottery-like stock than institutional and foreign investors do. Following Goetzman and Zhu (2005); Trading Volume, Net Buy, and Buy-Sell Imbalance are used as an investor trading behavior measures. We employ the investor-initiated trades to capture the trade pressure exerted by investors. Since the initiation makes the trade possible, this trade usually recognized as the price setting trade.

Table 2 summarizes the percentage of average daily trading activity across different investor types on three types of stock; lottery-like stock, nonlottery-like stock, and other stock. Panel A presents the percentage of daily trading in volume. Relative to the market, retail investors significantly prefer trading in the lottery-like stocks. Percentage of their lottery-like stocks initiate-trade is almost 70% of the total daily trade, while institutional investors initiate lottery-like stock trade about 54.58% and foreign investors initiate lottery-like stock trade about 42.70% daily. We can observe clearly that only retail investor initiate lottery-like stock trades more than the market (63.33%) and than other investor types. In contrast, the percentage of daily initiate trade in nonlottery-like stocks of retail investors (5.81%) is significantly lower than the market (9.88%) and than other investor types (16.95% and 22.61% for institutional and foreign investor, respectively). Interestingly, only retail investors trade nonlottery-like stock less than the market. Corresponding to nonlottery-like stock, percentage of their daily trading volume in the other stock is also less than the market and than other investor types.

Panel B presents the percentage of daily trading in value (baht). The results confirm that on average, retail investors initiate more of the lottery-like stocks trade, while behavior of institutional and foreign investor rather different, they trades more of the nonlottery-like stocks. Figure 1 displays the average daily trading in volume (Figure 1A) and in value (Figure 1B). Figure 2 illustrates the time-series plot of the percentage of lottery-like stock trading value relative to the total stock trading across different investor types. This figure shows the proportions of lottery-like stock traded by each investor types for each day of their trades. There are 2,451 trading days during our sample period. Retail investors obviously show their preference on lottery-like stock trade while foreign investors show less preference on lottery-like stock among three investor types.

We further investigate the retail investor tendency to buy lottery-like stocks relative to the nonlottery-like stocks (by volume and value). Table 3 presents the mean difference in daily net buy of lottery-like and nonlottery-like stocks. The daily net buy of a particular day is defined as the buy-initiated volume (value) minus the sell-initiated volume (value) by each investor on that day. In both Panel A and B, only retail investors exhibit the tendency to buy lottery-like stock. The mean difference of net buy is 301,855 in volume with *t-statistic* = 9.33 and 808,051 in value with *t-statistic* = 5.94. While the institutional and foreign investors show the tendency to sell the lottery-like stock. The mean difference of the net buy is -79,802 in volume with *t-statistic* = -3.04 for institutional investors and -48,322 in volume with *t-statistic* = -2.94 for foreign investors. Interestingly, the mean differences of net buy in value of institutional and foreign investors are statistically insignificant.

Table 4 reports an examination of Buy-Sell imbalance (BSI) and the mean difference in BSI across different stock types for each investors group. Similar to Kumar and Lee (2009) and Odean 2002, we define the buy-sell imbalance as the buying trades minus the selling trades relative to the total buying and selling trades. Positive (negative) BSI means investor are net buyers (sellers) during a particular day. Panel A shows that retail investors are the net buyers for lottery-like, nonlottery-like, and other stocks, while the institutional investors are the net sellers for those three types of stock and foreign investors are the net sellers of lottery-like stock but they are the net buyers for nonlottery-like and other stocks. Tests of the differences in mean of BSI indicate that retail investors significantly initiate more buy order of the lottery-like stock relative to nonlottery-like and other stock. The mean difference of BSI between lottery-like and nonlottery-like stock is 0.0361 with *t-statistic* = 2.54 and between lottery-like and other stock is 0.0057 with *t-statistic* = 1.97. In contrast, institutional and foreign investors initiate more sell order of lottery-like stock relative to other groups of stock, nevertheless the mean difference of BSI is not statistically significant for institutional investors. These results are confirmed in Panel B when the value BSI is examined.

We next perform the regressions of trading activity and BSI across different stock types for each investor groups. Table 5 reports the results of our first regression. For retail investors, the dummy stock-types coefficients are statistically significant. It is positive for lottery-like stocks but negative for nonlottery-like stocks. As expected, lottery-like stocks initiated-trading volume is significantly higher for retail investors, while nonlottery-like initiated-trading volume is negative (estimated coefficient = 0.0526 *t-statistic* = 3.17 and -0.1685 *t-statistic* = -7.33 for lottery-like and nonlottery-like stocks, respectively). The initiated-trading volume of lottery-like stocks of institutional and foreign investors is negative (estimated coefficient = -0.1355 *t-statistic* = -3.83 and -0.1530 *t-statistic* = -6.59 for institutional and foreign investors, respectively). We then investigate the trading activity in value (baht) for each investor groups, results provided in Panel B are similar to Panel A for the lottery-like stock trading activity across investor types. The nonlottery-like stock coefficient is positive foreign investors but insignificant for institutional investors.

Table 6 provides the coefficients estimation of BSI on different stock types. For retail investor, the estimated coefficients for lottery-like stock (b_1) are positive and statistically significant (estimated coefficient = 0.0098 *t-statistic* = 2.15 in Panel A and 0.0007 *t-statistic* = 2.21 in Panel B), which offers additional evidence that retail investors' BSI is higher for lottery-like stock, or they are the net buyers of the lottery-like stocks. In contrast, the estimated coefficients (b_1) are significantly negative for institutional and foreign investors (estimated coefficient = -0.0812 with *t-statistic* = -4.08 and -0.0336 with *t-statistic* = -2.77). Interestingly, the estimated coefficients of nonlottery-like stocks (b_2) are negative and insignificant for retail investors but positive and significant for institutional investors.

In sum, we observe that relative to institutional and foreign investors, retail investors initiate more of lottery-like stocks trade, they exhibit tendency to buy lottery–like stocks, and they are the net buyers of lottery-like stocks. These evidences consistent with Kumar (2009) that individual investor prefer stocks with lottery features and Baker and Wurgler (2005) that the subset of stocks which share most attributes with lottery-like stocks are most responsive to retail investors.

6.1.2 Investor Sentiment and the Macroeconomic Condition

Lottery studies propose that the popularity of lottery-playing and gambling increased dramatically during bad economic times (Brenner and Brenner (1990)). To examine whether investor propensity to invest in the lottery-like stock is analogous to the demand in lottery ticket during economic recession we run the time-series regression of investor sentiment shift on the macroeconomic variables. The regression specification takes into account both the macroeconomic conditions and the market and lottery-like stock returns.

Table 7 reports the time series regression estimated results of investor sentiment shift (EBSI) and the macroeconomic variables. During our ten-year sample period of study, the monthly unemployment rates are varied in the range of 0.85 to 5.73% and the growth in industrial productions varied between -11 to 8.7%. These figures illustrate the rise and fall of Thai economy during our sample period. For retail investor, only the lagged MPI is statistically significant, its coefficient is negative in both model 1 and 3. The results demonstrate that the lower growth in industrial productions are associated with the higher shifts in retail investors sentiment for the lottery-like stocks (EBSI) (estimated coefficient = -0.3327 (-0.2302), *t-statistic* = -2.80 (-1.93) in model 1 (3)). This evidence indicates that retail investor's propensity to buy a lottery-like stock increases during the bad economic time which is similar to the demand of lottery-tickets.

For institutional investor, the lagged lottery-like stock return is significantly positive in both model 2 and 3 with the estimated coefficient = 0.1932 (0.3350), *t-statistic* = 1.72 (2.23) in model 2 (3). This result indicates that institutional investor sentiment shift in the lottery-like stock is positively correlated with the previous lottery-like stock returns. Interestingly, the macroeconomic variables cannot explain any relative demand shifts for lottery-like stock of institutional investors. For foreign investors, there are three variables that statistically significant; the lagged MPI, the market return, and the lottery-like stock return. The results point out that foreign investor's relative demand shifts for lottery-like stock is greater with the higher MPI, lower market return and higher lottery-like stocks. Collectively, the regression results show that only retail investors display the similar tendencies in their lottery-like stocks trading and lottery ticket playing.

6.1.3 Lottery-like Stock Portfolio Performance

Results from section 6.1.1 and 6.1.2 demonstrate that, relative to the other investor types, retail investors exhibit the stronger preference for lottery-like stocks and their preference is greater during the economic recession. It is possible that retail investors may have informational advantage on the lottery-like stock. If investors have informational advantage, they should be able to identify the lottery-like stocks with superior performance and generate higher returns from their lottery-like investment. Analogous to the lottery players who think they know the nice number to win the jackpot. In contrast, if their preference in lottery-like stock is driven by the gambling-motive, it could negatively influence their investment choices. With this motivation, we test our second hypothesis that the lottery-like stock return underperforms the nonlottery-like stock return using the four-factor model and the CAPM model.

Table 8 presents the monthly performance of three equally weighted portfolios; lottery-like stocks, nonlottery-like stocks, and other stocks. Panel A reports the risk-adjusted performance differential between lottery-like stock portfolio and nonlottery-like stock portfolio using four-factor model. The performance differential between lottery-like stock portfolio and the other stocks portfolio also reported. The risk-adjusted performance (α_0) of the lottery-like portfolio is negative as expected but insignificant. The performance of nonlottery-like stock and other stock portfolios (α_0) are positive but also insignificant. The signs of the α_0 of the three stock portfolios come out as we expect which indicate that the risk-adjusted performance of the lottery-like stock portfolio is lower than those of the nonlottery-like stocks and the other stocks portfolio but they are statistically insignificant.

In Panel B, we use the CAPM model to estimate the monthly risk-adjusted performance. Predictably, the nonlottery-like stock portfolio performs better than the lottery-like stock portfolio. The performance estimates indicate that the lottery-like stock portfolio create significantly lower average monthly return relative to the nonlottery-like stock portfolio (the differential estimated coefficient = -0.0049, *t-statistic*s = -1.83). This is about 5.88% annually. According to CAMP model, stock market gamblers are paying expensive costs for their gambling motivated trading.

Table 9 provides the mean monthly portfolio returns of lottery-like and nonlottery-like stocks across three investor types. The performance estimates indicate in Panel A that lottery-like stocks portfolio of retail investors earn significantly lower monthly returns, relative to both institutional and foreign investors' lottery-like stock portfolios. Specifically, relative to institutional investors' portfolio, the monthly portfolio returns difference is -0.6195 or -7.434% annually. Relative to foreign investors' portfolio, the monthly portfolio returns difference is -0.7359 or -8.831% annually.

In Panel B, the performance estimates show that nonlottery-like stock portfolio of retail investors earn higher average returns relative to institutional investors but lower than that of foreign investors. Nevertheless, the mean differences are insignificant in both cases. Collectively, these performance estimations suggest that gambling-motivated trading have negative impact to retail investors' portfolio.

6.2 Gambling Seasonality in Thai Stock Market

This section aims to present (i) whether retail investors show different preference of lottery-like stock during different time periods, (ii) whether the lottery-like stocks return increases during the time period that gambling demand of investors is higher, and (iii) whether there is a relationship between investor sentiment and lottery-like stock returns.

6.2.1 Gambling Seasonality and Investor Behavior

Section 6.2.1 aims to test our third hypotheses since the behavioral alternative hypothesis suggests that individual may exhibit different gambling mentality in different period of time. We link the variation in gambling demand with (i) the famous market anomalies, i.e., Monday and January effect, (ii) the calendar effect i.e., Day-of-the-Week effect and Month-of-the-Year effect, (iii) the Market extremely moves, and (iv) the football outcome effects. Our prediction is that retail investors initiate more of lottery-like stock trades and are the net buyers on these four events of interest.

We also employ the GJR-GARCH (Glosten, Jagannathan, and Runkle (1993)) model to capture the seasonal effect in the returns across different stock types. The GJR-GARCH model is a modified GARCH-M model by allowing the seasonal patterns in volatility and letting the positive and negative innovations to returns having different impacts on conditional volatility. Specifically, this model is used to examine our hypothesis 3_{a2}, 3_{b2}, 3_{c2}, and 3_{d2} that whether the performance of lottery-like stocks is higher in the time period that gambling demand of investors is stronger.

6.2.1.1 Gambling Seasonality and the Market Anomaly

We investigate investor trading activity on Monday relative to that of on Non-Monday and expect to observe the higher demand of lottery-like stock from retail investors on Monday than on Non-Monday. Table 10 reports the difference in means of buy-initiated and sell-initiated between Monday and Non-Monday of different stock-types for each investor groups. Overall, results in Panel A shows that investors initiated less trades (both on buy-side and sell-side) on Monday relative to Non-Monday except that retail investor initiates more of sell orders of lottery-like stock on Monday than on Non-Monday (difference = 366,731 *t-statistic* = 1.97). We further analyze the tendency to buy the lottery-like stocks on Monday relative to Non-Monday. Panel B presents the mean difference in daily net buy between Monday and Non-Monday of different stock types for each investor groups. Results indicate that retail investors exhibit fewer tendencies to buy stock on Monday. The mean differences of net buys are significant and negative for all three types of stocks. While the mean difference of net buy of institutional investors is insignificant. For foreign investors, the mean difference of net buy is significant and negative for nonlottery-like and other stocks.

Table 11 reports the results of our trading volume regression. For retail investors, the estimated coefficients (b_1) are negative but insignificant (estimated coefficient = -0.0405, *t-statistic* = -1.51). The Monday initiated-trading volume of lottery-like stock of institutional and foreign investors is also insignificant. There is no evidence of higher gambling demand on Monday across different investor types. Table 12 provides the coefficients estimation of Monday BSI for each investors group. For retail investors, the coefficients for lottery-like stock are negative and statistically significant (estimated coefficient = -0.0125, *t-statistic* = -1.82), which suggests that retail investors are the net sellers of the lottery-like stocks on Monday. In contrast, the lottery-like stocks' coefficients are insignificantly negative for institutional and foreign investors. This is opposing to our prediction since we expect to observe that retail investors as the net buyers of lottery-like stock on Monday.

Table 13 reports the results of our trading volume regression for January trading analysis. Results show that retail and institutional investors initiated less lottery-like stocks trade in January (estimated coefficient = -0.2433 *t-statistic* = -4.14, -0.1729 *t-statistic* = -2.11, respectively). Table 14 provides the BSI regression results for each investor types on January. We expect to observe the estimated coefficient (b_1) of lottery-like stock of retail investors to be significant and positive. All estimated coefficients (b_1) of lottery-like stock are insignificant for all three types of investor. Collectively, there is no evidence that retail investors' demand for lottery-like stocks is higher on Monday or in January.

To observe whether the gambling motive influence investor trading decision differently on Monday and in January, we run GJR-GARCH model. Table 15 reports the estimated results for Monday and January effect. In Panel A, the Monday effect coefficients (α_1) are significantly negative regardless of the types of stock, showing that the Monday effect persists in Thai stock market. Interestingly, the effect is stronger in lottery-like stocks (coefficient = -0.0053, *t-statistic* = -5.35) than in nonlottery-like stocks and in the other stocks (estimated coefficient = -0.0033, *t-statistic* = -6.18, coefficient = -0.0035, *t-statistic* = -5.30, for nonlottery-like stocks and the other stocks, respectively). This is contrary to our prediction since we expect to observe the estimated coefficient (α_1) of lottery-like stock to be positive and significant.

In Panel B, the January effect coefficients are (α_1) positive for all three types of stock but they are insignificant. Nevertheless, the January effect is strongest in lottery-like stock return. Overall, results indicate that selling pressure from retail investors can be the root of Monday effect in Thai stock market but we find no association between gambling demand and Monday or January effects.

6.2.1.2 Gambling Seasonality and the Calendar Effect

Table 16 reports the BSI regression for each day of the week. For retail investors, the lottery-like stocks estimated coefficients are significant and negative on Monday (estimated coefficient = -0.0057, *t-statistic* = -2.51) and positive but insignificant on the other weekdays. Whereas the estimated coefficients of institutional investors are a negative and significant for Tuesday, Wednesday, and Friday (estimated coefficient = -0.1191, *t-statistic* = -3.91, estimated coefficient = -0.0591, *t-statistic* = -2.34, and estimated coefficient = -0.0681, *t-statistic* = -2.24, respectively) and the estimated coefficients of foreign investors are significant and negative only on Tuesday. We illustrate the Day-of-the-Week pattern for daily net buy of different investor types in Figure 3.

To observe whether the gambling motive influence investor trading decision differently during different Calendar time (i.e. Day-of-the-week, Month-by-Month), we run GJR-GARCH model for each day of the week and each month of the year. Table 17 reports the Day-of-the-Week analysis. We expect to observe the weekday dummy variable estimated coefficients of the lottery-like stock to be positive and significant. The results show that only Monday estimated coefficients are significantly but they are negative. Other weekday coefficients of lottery-like stocks are insignificant. There is no evidence of Day-of-the-Week return seasonality in the lottery-like stock. Interestingly, the results provide a strong evidence of significant positive Friday returns in nonlottery-like and other stocks but not in the lottery-like stocks return. This Friday effect evidence in Thai stock market is consistent with the study of Kamath et al. (1998) and Holden et al. (2001).

Table 18 provides the results of Month-by-Month analysis of Buy-Sell imbalance regression. The results of retail investors analysis show that they are the net-sellers for lottery-like stock in March, August, and October and they are the net-buyers for lottery-like stock in June. Interestingly, the estimated coefficient of institutional investors is significant and positive for December dummy. This implies that institutional investors are the net buyers of lottery-like stocks in December. While the estimated coefficient of lottery-like stock of foreign investors are insignificant. Figure 3 illustrates the Month-by-Month pattern of the net buy across different investor types.

Table 19 Panel A reports the Month-by-Month analysis. The lottery-like stocks' estimated coefficients are significant and negative for five months; March, July, August, October, and November and significantly positive for June and December. While the coefficients of nonlottery-like stocks are all insignificant, indicating that there is no evidence of the Month-by-Month return seasonality in nonlottery-like stock. Panel B reports January and Non-January analysis. Only the Non-January coefficient of lottery-like stock is significant and negative, indicating the underperformance of lottery-like stock for Non-January months. We further investigate investors' trading activities for June and December, the months that lottery-like stock returns are positive and significant.

Table 20 shows the mean difference of buy-initiated (sell-initiated) between June and Non-June in Panel A and the mean differences of net buy between June and Non-June in Panel B. The result shows that only retail investors exhibit the tendency to buy more of lottery-like stocks in June than in Non-June month. Table 21 presents the regression results of investor trading volume in June. The estimated coefficients indicate that retail and institutional investors initiate more of lottery-like stock trade in June. Table 22 reports the BSI regression results. Only estimated coefficient of retail investors are significant and positive for lottery-like stock in June (estimated coefficient = 0.0249, *t-statistic* = 2.19), implying that only retail investors are the net buyers of lottery-like stocks in June.

Table 23 Panel A shows that only institutional investors initiate to buy more of the lottery-like stocks in December. Panel B displays that institutional investors exhibit the higher net buy of lottery-like stock in December. Table 24 reports the significant and positive estimated coefficients of lottery-like stocks of institutional investors, implying that only institutional investors initiate more of lottery-like stock trades in December. Table 25 confirms that institutional investors are the net buyers of lottery-like and nonlottery-like stock in December (estimated coefficient = 0.1467, *t-statistic* = 2.57 and estimated coefficient = 0.1185, *t-statistic* = 2.87 for lottery-like and nonlottery-like stock, respectively).

Collectively, we observe that retail investors exhibit higher demand of lottery-like stock in June while institutional investors demand more of lottery-like stock in December.

There is no difference in demand level of lottery-like stock of foreign investors. The outperformance of lottery-like stock in June and December is associated with the high demand in lottery-like stock of retail investors in June and the high demand in lottery-like stocks of institutional investors in December. Institutional investors' high demand in lottery-like and nonlottery-like stocks in December should be the buying pressure form the tax-deductible fund, namely RMF (Retirement Mutual Fund) and LTF (Long-Term Equity Fund) as the year end is approaching.

6.2.1.3 Gambling Seasonality and the Market Moves

Table 26 reports the regression results of investors' trading volume on the trading day that the Market increases more than 3%. During our sample period of ten years, there is 69 (73) days that the Market increases (decreases) more than 3%. We also consider the 2% increases (decreases) as the cutting point. There are 198 (192) trading days that the Market increases (decreases) more than 2%. The regression results are similar whether we use 2% or 3% as a cutting point. Panel A reports the estimation of trading volume on the day that the market increases more than 3%. The lottery-like stock estimated coefficient (b_1) is significant and negative for retail and foreign investors (estimated coefficient = -0.5278, *t-statistic* = -5.09 and estimated coefficient = -0.2411, *t-statistic* = -2.15). For institutional investors, the b_1 of lottery-like stock is insignificant. Panel B reports the result for the trading day that market decreases more than 3%. We expect to observe the gambling demand of retail investors is higher on the day that the Market decreases more than 3% or the b_1 for lottery-like stock is significant and positive. But the estimated coefficients are negative (estimated coefficient = -0.2169, *t-statistic* = -2.09). Table 27 reports the BSI regression estimations. Results in Panel A show that retail investors are the net sellers of lottery-like and nonlottery-like stocks on the day that the Market extremely increases, while institutional investors are the net buyers for nonlottery-like and other stocks. Foreign investors are the net buyers for nonlottery-like stocks. Panel B shows the BSI estimations on the trading that the Market decrease more than 3%, the lottery-like stock estimated coefficients are insignificant. Collectively, there is no evidence of higher gambling demand from retail investors on the trading day that the Market extremely decreases. We also expect to observe that of lottery-like stocks return is positive on the trading day that the market extremely decreases given that retail investors exhibit stronger preference for lotteries on the stock market losses than to stock market gains, i.e. we expect the α_1 of lottery-like stock in Panel B of Table 28 is significant and positive. The results in Table 28 report the significant and positive estimated coefficients (α_1) of all stock-types on the trading day that the market increases more than 3% (Panel A) While α_1 of all stock-types on the trading day that the market decreases more than 3% is significant and negative in Panel B. We further investigate whether the gambling motivated trade affects the stock return later after the Market extremely moves. Table 29 reports the estimated results on the trading day after the market extremely moves. The α_1 of lottery-like stocks and nonlottery-like stocks are insignificant in both Panels. Overall, there is no evidence of return seasonality in the lottery-like stock on the trading day that the market extremely moves and the trading day after the market extremely moves.

The GJR-GARCH frameworks utilized in this section also capture the asymmetric effect of shocks on the conditional volatility. The γ is negative and significant in all estimated regressions, indicating that the positive shocks have larger impacts on the conditional variance. The conditional volatility in Thai stock market tends to be lower when the news is unfavorable. This finding is consistent with the study of Chang, Nieh, Yang, and Yang (2006) in the Taiwan stock market, where the retail investor concentration is very high. Furthermore, the δ of the lottery-like stock is greater than that of the nonlottery-like stock, signifying that more recent news has greater impact on lottery-like stock returns than on nonlottery-like stock return. While the θ indicates that impact of past variance on nonlottery-like stock return of stock is higher than on the lottery-likes stock return.

6.2.2 Investor Sentiment and Lottery-like Stock Return Lead-Lag Relation

It is possible that investor sentiments have an effect on the lottery-like stock returns since high idiosyncratic volatility can be a observe as a proxy for high arbitrage cost of the stocks and investor sentiment may also be influenced by the returns of lottery-like stocks.

We utilize the bivariate vector-autoregression (VAR) model and the Granger causality tests to find out these dynamic relationships.

Table 30 presents the lead-lag relationship between the investor sentiment (BSI) and the lottery-like stock returns using the Vector Auto-Regression and Granger causality tests. We used AIC and SIC information criterion measures to identify the proper number of lags. Panel A reports the VAR estimated coefficients. The results indicate that the dynamic relationships between BSI and lottery-like stock returns are existed for retail and institutional investors. Initially, the coefficient = 0.9382, *t-statistic* = 3.42 for retail investors and coefficient = 0.6956, *t-statistic* = 2.83 for institutional investors evidence that their trades are influenced by lottery-like stock returns, with the higher sensitivity for retail investors than for the institutional investors.

More importantly, the prior BSI has ability to predict lottery-like stock return in all three models (the estimated coefficient = 0.0002, *t-statistic* = 1.95 for retail investors, estimated coefficient = 0.0003, *t-statistic* = 1.89 for institutional investors, and the estimated coefficient = -0.0002, *t-statistic* = -1.84 for foreign investors). Taken as a whole, the bivariate VAR model suggest that retail and institutional investors' BSIs are positively influenced by lottery-like stock returns and their BSIs also influence the lottery-like stock returns. Based on Granger causality tests, Panel B examines the causal relation between the prior investor BSI and current lottery-like stock returns, and between the prior lottery-like stocks return and current investor BSI. Corresponding to VAR model, the results indicate that we fail to reject the Granger causality null hypotheses that BSI is non Granger cause the lottery-like stock return and lottery-like stock return non Granger cause the BSI for all three investor types.

In sum, we therefore come to the following six conclusions from our analysis.

1. Relative to institutional and foreign investors, retail investors exhibit the stronger preference in lottery-like stocks.
2. Only retail investors display the similar tendencies in their lottery-like stock trading and lottery playing.

3. The lottery-like stock portfolio of retail investors significantly underperforms the lottery-like stock portfolio of institutional and foreign investors.
4. Retail investors initiate more of lottery-like stock trades and are the net buyers of lottery-like stocks in June while Institutional investors initiate more of lottery-like stock trades and are the net buyers of lottery-like stocks in December. There is no significant difference in gambling demand level of foreign investors.
5. Lottery-like stock return outperforms the nonlottery-like stock return in Junes and Decembers.
6. There is a significant positive dynamic relation between retail and institutional investors' BSI and the lottery-like stock returns.

CHAPTER VII
CONCLUSION

This study investigates two research issues. First, we explore whether retail investors' trading motives are influenced by gambling preference. Given that, on average, retail investors are presumed to have more behavioral bias than other types of investors are. Second, we examine whether there is a gambling seasonality in Thai stock market. Since, evidences from gambling and individual risk taking suggest that investors may exhibit different gambling mentality in different periods of time. We use transactional trading data of all individual stocks traded on the Stock Exchange of Thailand (SET) over the sample period form January 1999 to December 2008.

Using several measures of investor trading activity, we find that retail investors initiate more of lottery-like stock trades than institutional and foreign investors do. Retail investors are the net buyers of lottery-like stocks while institutional and foreign investors are the net sellers of lottery-like stocks. This evidences that, relative to institutional and foreign investors, retail investors exhibit the stronger preference for lottery-like stocks. Furthermore, their propensity to invest in lottery-like stocks increase during the economic recession which is similar to the demand in lottery tickets. We further find out that retail investors' preference in lottery-like stock is driven by the gambling-motive rather than the informational advantage. The behavioral bias, i.e. illusion of control, leads people to think that they can control random events. This bias leads stock traders to believe that their chosen better stocks. Our results from portfolio performances analysis suggest that gambling-motivated decision negatively influences investor's portfolio performance.

Our analyses on the gambling seasonality indicate that selling pressure from retail investors is the rooted of Monday anomaly in Thai stock market but there is no association with the gambling demand from retail investors on Monday. We evidence that retail investors initiate more of lottery-like stock trades and they are the net buyers of lottery-like stock in June while institutional investors initiate more of lottery-like stock and they are the net buyer of lottery-like in December. Foreign investors do not exhibit any differences in demand level for lottery-like stocks during different time periods. The promising explanation for institutional investors' high demand in lottery-like stock in December should be the buying pressure form the tax-deductible fund, namely RMF (Retirement Mutual Fund) and LTF (Long-Term Equity Fund) as the year end is approaching. Thai investors (around 70 – 75%) often buy into the LTF and RMF funds in the forth quarter of the year, while most choose to invest in December (KE live research (2010)). According to Association of Investment Management Companies (AIMC), net new fund flow into the LTF in December is 86.66% of the total net new fund flow in 2010, (69.27% of total net new fund flow in 2009) while the net new fund flow into the RMF in December is 60.87% of the total net new fund flow in 2010 (68.38% in 2009).

Conclusions from the bivariate vector-autoregression (VAR) model display the positive dynamic relation between retail and institutional investors' BSI and the lottery-like stock returns, implying that investor sentiments have an effect on the lottery-like stock returns and investor sentiment is also influence by the returns of lottery-like stocks. Interestingly, our results from GJR-GARCH model evidence the significantly negative return of lottery-like stock in Non-January month. The Month-by-Month return analysis shows the positive returns of lottery-like stock in Junes and Decembers. Taken into account the dynamic relation of investor sentiment and lottery-like stock return, the positive returns seasonality in lottery-like stocks are corresponding with the retail investors' high demand of lottery-like stock in June and with the institutional investors' high demand of lottery-like stock in December. We conjecture that retail investors cause return seasonality in June due to their behavioral bias, i.e. illusion of control. This gambling seasonality appears to be persuasive evidence against the efficient market hypothesis.

Our results suggest a number of interesting implications. Firstly, for academic, we exploit gambling behavior to explain people behavior in different setting, i.e. the stock market, and offer evidences of behavioral bias in the emerging stock market. Secondly, our findings that gambling preferences could be harmful to the portfolio performance should increase investor awareness. This suggests that to be a successful investors, individual has to overcome behavioral biases. Thirdly, our results recommend the investment advisors to incorporate behavioral issues as risk factors to formulate effective investment strategies for retail investors. Finally, our findings shows the deviation from the expected utility theory, policy makers might enhance investor's financial literacy and improve investor's protection.

In this study, we use a transaction data which includes the complete trading records of all investors in Thai stock market over a ten-year period. This data set offers a clear identification of which investor types trades the stock. The outstanding richness of these data allows a uniquely detailed examination of the trading behavior of retail, institutional, and foreign investors. However, the dataset do not provide a detail accounting holdings or the portfolio position data for each investor. We can observe only the aggregate trading behavior across investor types.

Taken as a whole, this study suggests the relation between behavioral bias and stock market trading behavior. This evidence emphasizes the need for more discussion in the finance academic society of both the implications and intentions that apply to the Efficient Market Hypothesis. As the level of gambling activity in society increases, the level of behavior bias in the stock market may possibly increase. The future study should incorporate behavioral factors when investigate the stock market behavior.

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APPENDICES

APPENDIX A

Table 1
Basic Characteristics of the Lottery-Like Stocks

This table presents the basic characteristics of lottery-like stocks, nonlottery-like stocks, and other stocks determined during the sample period from January 1999 to December 2008. All stocks in the Stock Exchange of Thailand are examined. The lottery-like stocks are the stocks in the lowest price percentile, highest idiosyncratic volatility percentile, and highest idiosyncratic skewness percentile. The nonlottery-like stocks are the stocks in the highest price percentile, lowest idiosyncratic volatility percentile, and lowest idiosyncratic skewness percentile. The stocks that do not belong to either of the two groups are classified as the other stocks. Panel A reports the mean monthly characteristics and Panel B presents descriptive statistics of daily return across different stock types.

Panel A: Mean monthly characteristics

Measure	Lottery-like	Nonlottery-like	Other stocks
Number of stocks (stock-months)	963	961	4,397
Percentage of the total stocks	15.23%	15.20%	69.56%
Percentage of the market	4.01%	25.98%	70.01%
Average stock price (baht)	5.63	43.29	18.35
Average firm size (in million baht)	4,791	17,444	10,430
Idiosyncratic volatility	0.0553	0.0201	0.0343
Total volatility	0.0587	0.0403	0.0394
Idiosyncratic skewness	0.0997	-0.0485	0.0701
Total skewness	0.1728	0.0721	0.0851
Systematic skewness	0.0058	0.0014	0.0034
Market beta	0.0054	0.0008	0.0035
SMB beta	-0.0016	-0.0003	-0.0007
HML beta	0.0007	0.0002	0.0004
WML beta	0.0011	0.0002	0.0005
Monthly mean return	0.713%	0.925%	0.831%
Monthly volume turnover	20.81%	1.14%	6.52%
Amihud illiquidity ratio	17.58	2.02	8.54
$(1-R^2)$	0.5741	0.3749	0.4446

Panel B: Daily return descriptive statistics

Daily return	Lottery-like	Nonlottery-like	Other stocks
Mean	0.00019	0.00028	0.00021
Median	-0.0066	0.0041	0.0011
Minimum	-1.8920	-0.3579	-0.9459
Maximum	2.9857	2.6712	2.7323
Standard Deviation	0.0614	0.0312	0.0459
Skewness	6.4264	0.1259	2.6118
Kurtosis	310.84	14.11	165.38

Table 2
Percentage of Daily Trading Activity

This table summarizes the percentage of the average daily trading volume and trading value during the sample period from January 1999 to December 2008. All stocks in the Stock Exchange of Thailand are classified into three types; lottery-like stock, nonlottery-like stock and the other stocks. Investors are classified into four groups; Retail investor, Institutional investor, Foreign investor, and Broker-owned portfolio. Panel A reports the percentage of the average daily trading volume in share of each investor group for the different stock types. Panel B reports the percentage of the average daily trading value in baht of each investor group for the different stock types. The percentage of the average daily trading of the whole market (all investors) and the number of stock-days also report.

Panel A: Percentage of daily trading volume (%)

Stock-types	Stock-days	Retail	Institution	Foreign	Broker	All investors
Lottery-like	76,488	69.61	54.58	42.70	50.98	63.33
Nonlottery	71,787	5.81	16.95	22.61	17.10	9.88
Other	336,262	24.58	28.47	34.69	31.92	26.80
All stocks	484,537	100%	100%	100%	100%	100%

Panel B: Percentage of daily trading value (%)

Stock-types	Stock-days	Retail	Institution	Foreign	Broker	All investors
Lottery-like	76,488	33.93	15.50	8.58	8.06	20.70
Nonlottery	71,787	29.78	42.49	51.88	41.28	39.33
Other	336,262	36.29	42.02	39.54	50.67	39.97
All stocks	484,537	100%	100%	100%	100%	100%

Table 3
The Mean Difference in Daily Net Buy of the Lottery-Like and Nonlottery-Like Stocks

This table reports the mean difference in daily net buy of the lottery-like and nonlottery-like stock of each investor types. The sample period is from January 1999 to December 2008. The daily net buy is computed as; $NB_{ijt} = \sum_{n=1}^{N} B_{ijt,n} - \sum_{m=1}^{M} S_{ijt,m}$ where NB_{jit} is the net buy of stock *i* by investor *j* on day *t*. *B* denotes buy-initiated volume (value) of stock *i* by investor *j* on day *t*. *S* denotes sell-initiated volume (value) of stock *i* by investor *j* on day *t*. *M* is the total number of buy-initiated trades on day *t*. *N* is the total number of sell-initiated trades on day *t*. The buy-initiated (sell-initiated) trade is defined as a trade where the buy-side (sell-side) order is received at the exchange later than the sell-side (buy-side) order. The mean daily net buy of the lottery-like and the nonlottery-like stock are reported in column A and B, respectively. The *t-statistics* for the means and the difference in means are presented in the parentheses.

Panel A: Daily net buy in volume

Investor	**Lottery-like (A)**	**Nonlottery-like (B)**	**Lot – Nonlot (A) – (B)**
Retail investor	306,334	4,478.8	301,855
	(7.98)	(2.71)	(9.33)
Institutional investor	-88,381	-8,578	-79,802
	(-5.87)	(-3.04)	(-3.04)
Foreign investor	-41,354	6,968.3	-48,322
	(-4.01)	(2.76)	(-2.94)

Panel B: Daily net buy in value

Investor	**Lottery-like (A)**	**Nonlottery-like (B)**	**Lot – Nonlot (A) – (B)**
Retail investor	1.07E6	262,440	808,051
	(6.77)	(4.53)	(5.94)
Institutional investor	-23,367	48,710	-72,076
	(-2.67)	(2.03)	(-1.04)
Foreign investor	-70,742	158,028	-229E3
	(4.98)	(6.98)	(-1.06)

Table 4
Buy-Sell Imbalance of Different Investor Types

This table presents the means of Buy-Sell imbalance (BSI) of different investor types. The sample period is from January 1999 to December 2008. The BSI is computed as $BSI_{jit} = \frac{(Buy_{jit} - Sell_{jit})}{(Buy_{jit} + Sell_{jit})}$. BSI_{jit} denotes the Buy – Sell imbalance of stock i by investor j on day t. Buy_{jit} is buy-initiated volumes (value) for stock i of investor j on day t. $Sell_{jit}$ is sell-initiated volumes (value) for stock i of investor j on day t. The *t-statistics* for the mean differences across different stock types for each investor group are presented in the parentheses.

Panel A: Average daily BSI volume

Investor	Lottery-like (A)	Nonlottery (B)	Other stocks (C)	Test of (A) – (B)	Test of (A) – (C)
Retail investor	0.0421	0.0060	0.0365	0.0361 (2.54)	0.0057 (1.97)
Institutional investor	-0.0853	-0.0400	-0.0366	-0.0454 (-1.49)	-0.0487 (-1.57)
Foreign investor	-0.0478	0.0221	0.0081	-0.0699 (-2.01)	-0.0559 (-1.93)

Panel B: Average daily BSI value

Investor	Lottery-like (A)	Nonlottery (B)	Other stocks (C)	Test of (A) – (B)	Test of (A) – (C)
Retail investor	0.0481	0.0135	0.0387	0.0346 (3.65)	0.0094 (1.65)
Institutional investor	-0.0112	-0.0086	0.0065	-0.0025 (-1.09)	-0.0177 (-1.98)
Foreign investor	-0.0181	0.0142	0.0087	-0.0323 (-2.76)	-0.0269 (-2.13)

Table 5
Investor Daily Trading Activity and Stock-Types

The table reports the estimated coefficients of the following time-series regression;

$$ln(Total\ trading\ activity)_{j,t} = b_0 + b_1 DummyLot_{j,t} + b_2\, DummyNonLot_{j,t} + b_3\, StockPrice_{j,t} + b_4\, MktRet_{j,t} + b_5\, MktRet_{j,t\text{-}1} + b_6\, lnSETVol_{j,t} + b_7\, lnSETVol_{j,t\text{-}1} + b_8 ln(Total\ trading\ activity)_{j,t\text{-}1} + \varepsilon_{j,t}$$

In Panel A (Panel B), *Total trading activity*$_{j,t}$ is volume (value) buy-initiated plus volume (value) sell-initiated by investor *j* on day *t*. *DummyLot*$_{j,t}$ is a dummy variable set equal to one for lottery-like stock and equal zero otherwise. *DummyNonLot*$_{j,t}$ is a dummy variable set equal to one for nonlottery-like stock and equal zero otherwise. *StockPrice*$_{j,t}$ is the price of stock *i* on day *t*. *MktRet*$_{j,t}$ is the stock market return on day *t*. *MktRet*$_{j,t\text{-}1}$ is the stock market return on day *t-1*. *SETVol*$_{j,t}$ is the market trading volume on day *t*. *SETVol*$_{j,t\text{-}1}$ is the market trading volume on day *t-1*. *Total trading activity*$_{j,t\text{-}1}$ is Total volume (value) purchased and sold by investor *j* on day *t-1*. $\varepsilon_{j,t}$ is a mean-zero error term. The sample period is from January 1999 to December 2008. The White Heteroskedasticity Consistent Estimators for standards errors are employed. The *t-statistics* are provided in the parentheses below the estimated coefficients.

Panel A	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	$Adj.R^2$
Retail investor	0.3101	0.0526	-0.1685	-0.0041	0.9996	0.9983	0.8478	-0.6565	0.7977	90.02%
	(4.16)	(3.17)	(-7.33)	(-5.10)	(2.99)	(3.06)	(7.27)	(-8.06)	(13.74)	
Institutional investor	-0.5554	-0.1355	-0.1169	-0.0035	0.9428	-0.0201	0.7431	-0.2148	0.4543	57.95%
	(-3.43)	(-3.83)	(-2.56)	(-2.10)	(1.33)	(-2.93)	(8.40)	(-6.14)	(12.75)	
Foreign investor	0.4364	-0.1530	-0.0685	-0.0023	0.3183	-0.7111	0.7469	-0.3732	0.5728	72.53%
	(4.21)	(-6.59)	(-2.23)	(-2.02)	(2.82)	(-1.56)	(12.83)	(-7.89)	(15.58)	
Panel B	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	$Adj.R^2$
Retail investor	0.5783	0.0532	-0.0911	0.0015	0.9792	0.0731	0.7231	-0.6059	0.8059	82.53%
	(3.98)	(3.40)	(-4.37)	(1.98)	(6.29)	(3.49)	(7.32)	(-8.06)	(17.50)	
Institutional investor	0.4124	-0.7791	-0.0436	0.0048	-0.4195	-0.5821	0.5864	-0.1949	0.4252	60.42%
	(7.34)	(-8.94)	(-1.05)	(3.17)	(-0.65)	(-2.52)	(8.58)	(-6.15)	(9.46)	
Foreign investor	0.3017	-0.6548	0.0636	0.0042	-0.1508	-0.0369	0.5931	-0.3545	0.5853	79.60%
	(6.63)	(-4.25)	(2.14)	(3.89)	(-0.33)	(-0.08)	(7.05)	(-5.87)	(12.70)	

Table 6
Investors' Buy-Sell Imbalance and Stock Types

The table reports the estimated coefficients of the following time-series regression;

$$BSI_{j,t} = b_0 + b_1\,DummyLot_{j,t} + b_2\,DummyNonLot_{j,t} + b_3\,StockPrice_{j,t} + b_4\,MktRet_{j,t} + b_5\,MktRet_{j,t-1} + b_6\,lnSETVol_{j,t} + b_7\,lnSETVol_{j,t-1} + b_8\,BSI_{j,t-1} + \varepsilon_{j,t}$$

In Panel A (Panel B), $BSI_{j,t}$ denotes Buy-Sell imbalance in volume (value) of investor *j* on day *t*. $DummyLot_{j,t}$ is a dummy variable set equal to one for the lottery-like stock and equal zero otherwise. $DummyNonLot_{j,t}$ is a dummy variable set equal to one for nonlottery-like stock and equal zero otherwise. $StockPrice_{j,t}$ is the price of stock *i* on day *t*. $MktRet_{j,t}$ is the stock market return on day *t*. $MktRet_{j,t-1}$ is the stock market return on day *t-1*. $SETVol_{j,t}$ is the market trading volume on day *t*. $SETVol_{j,t-1}$ is the market trading volume on day *t-1*. $BSI_{j,t-1}$ is Buy-Sell imbalance in volume (value) of investor *j* on day *t-1*. $\varepsilon_{j,t}$ is a mean-zero error term. The sample period is from January 1999 to December 2008. The White Heteroskedasticity Consistent Estimators for standards errors are employed. The *t-statistics* are presented in the parentheses below the estimated coefficients.

Panel A	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	$Adj.R^2$
Retail investor	-0.1339 (-5.16)	0.0098 (2.15)	-0.0113 (-1.47)	0.9159 (-0.49)	0.9172 (7.12)	-0.3031 (-8.25)	0.0283 (4.95)	-0.0178 (-3.16)	0.0903 (7.71)	22.75%
Institutional investor	-0.2733 (-3.01)	-0.0812 (-4.08)	0.0564 (2.19)	-0.0008 (-0.84)	0.8754 (4.23)	-0.5874 (-4.05)	0.0477 (2.45)	-0.0303 (-1.57)	0.2678 (5.31)	10.55%
Foreign investor	-0.5558 (-4.04)	-0.0336 (-2.77)	-0.0065 (-0.40)	0.0004 (0.07)	0.7433 (7.11)	0.5137 (5.92)	0.0357 (2.99)	0.0018 (0.15)	0.2364 (8.05)	21.84%
Panel B	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	$Adj.R^2$
Retail investor	-0.0653 (-2.49)	0.0007 (2.21)	-0.0213 (-2.73)	-0.0001 (-0.04)	0.3805 (6.90)	-0.8388 (-4.61)	0.0220 (3.79)	-0.0159 (-2.77)	0.1217 (8.46)	19.50%
Institutional investor	-0.0223 (-0.26)	-0.1036 (-5.44)	0.0162 (0.66)	-0.0007 (-0.73)	0.5042 (3.13)	-0.9913 (-5.32)	0.0178 (0.96)	-0.0153 (-0.83)	0.2709 (5.61)	10.86%
Foreign investor	-0.3966 (-7.50)	-0.0342 (-2.94)	0.0009 (0.60)	-0.0002 (-0.42)	0.8915 (3.29)	0.6263 (6.55)	0.0305 (2.66)	-0.0037 (-0.32)	0.2602 (7.43)	24.74%

Table 7
Investor Sentiment Shift and the Macroeconomic Conditions

This table reports the estimated coefficients of the following time-series regression models;

$$EBSI_t = \beta_0 + \beta_1\, UnEmploy_{t-1} + \beta_2\, UnExpInf_{t-1} + \beta_3\, TS_{t-1} + \beta_4\, MPI_{t-1} + \beta_5\, MktRet_t + \beta_6\, MktRet_{t-1} + \beta_7\, LotRet_t + \beta_8\, LotRet_{t-1} + \beta_9\, EBSI_{t-1} + \varepsilon_t$$

$EBSI_t$ denotes the excess Buy-Sell imbalance on month *t*, where $EBSI_t = LBSI_t - NBSI_t$. $LBSI_t$ is the buy-sell imbalance of a portfolio of lottery-like stocks on month *t*. $NBSI_t$ is the buy-sell imbalance of a portfolio of the other remaining stocks on month *t*. $UnEmploy_{t-1}$ is the unemployment rate on month *t-1*. $UnExpInf_{t-1}$ is the unexpected inflation on month *t-1* ; the average of the 12 most recent inflation realizations is used to estimate the expected level of inflation. TS_{t-1} is the term spread on month *t-1*; the term spread measured as the difference between the yield of a 10-year Government bond and the yield of a 3-month Treasury bill. MPI_{t-1} is the monthly growth in industrial production on month *t-1*. $MktRet_t$ is the average monthly market return on month *t*. $MktRet_{t-1}$ is the average monthly market return on month *t-1*. $LotRet_t$ is the average monthly return of lottery-like stocks on month *t*. $LotRet_{t-1}$ *is* the average monthly return of lottery-like stocks on month *t-1*. ε_t is a mean-zero error term. The sample period is from January 1999 to December 2008. The White Heteroskedasticity Consistent Estimators for standards errors are employed. The *t-statistics* are presented in the parentheses below the estimated coefficients.

Investor	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	$AdjR^2$
Retail investor	0.8319	-0.0005	-0.2069	0.9022	-0.3327						5.35%
Model 1	(1.40)	(-0.01)	(-1.46)	(0.15)	(-2.80)						
2	0.0503					0.0743	-0.7948	0.0415	0.0156		1.34%
	(0.30)					(0.02)	(-0.27)	(0.94)	(0.36)		
3	0.5441	0.0167	-0.1415	0.0204	-0.2302	-0.1793	-0.6261	0.0089	0.0024	0.3035	10.81%
	(0.92)	(0.10)	(-1.00)	(0.01)	(-1.93)	(-0.06)	(-0.22)	(0.21)	(0.06)	(3.24)	
Institutional investor	1.6091	-0.7716	-0.4828	-30.3491	-0.9045						2.46%
Model 1	(0.71)	(-1.25)	(-0.89)	(-1.34)	(-1.63)						
2	-2.2923					3.6962	-0.2935	0.0750	0.1932		4.63%
	(-5.15)					(0.47)	(-0.04)	(0.66)	(1.72)		
3	1.3421	-0.8045	-0.0038	-28.5922	-0.6725	8.9359	-4.7526	0.1689	0.33501	0.2534	21.45%
	(0.65)	(-1.38)	(-0.01)	(-1.36)	(-1.52)	(0.88)	(-0.47)	(1.13)	(2.23)	(2.90)	
Foreign investor	-3.0803	0.5561	0.0944	6.6875	0.8141						6.36%
Model 1	(-2.42)	(1.60)	(0.31)	(0.52)	(3.20)						
2	-3.2352					-26.7147	0.5598	0.1894	0.0195		13.72%
	(-0.95)					(-4.41)	(0.09)	(2.16)	(0.23)		
3	-2.2584	0.3355	-0.0418	-0.8277	0.7753	-26.3952	2.1041	0.1797	-0.0021	0.0414	19.24%
	(-1.85)	(1.00)	(-0.14)	(-0.07)	(3.11)	(-4.45)	(0.32)	(2.07)	(-0.02)	(0.43)	

Table 8
Lottery-Like and Nonlottery-Like Stock Portfolio Performance

The table reports the monthly risk-adjusted performance of the lottery-like stocks, nonlottery-like stocks, and the other stocks equally weighted portfolios for the sample period from January 1999 to December 2008. In Panel A, the four-factor time-series models are estimated;

$$R_{p,t} - R_{f,t} = \alpha_0 + \beta_{1p}RMRF_t + \beta_{2p}SMB_t + \beta_{3p}HML_t + \beta_{4p}WML_t + \varepsilon_{p,t}$$

$R_{p,t}$ denotes the monthly rate of return of portfolio *p*. $R_{f,t}$ denotes the risk-free rate which is Thailand's one-month Inter-bank rate. $RMRF_t$ is the market return in excess of the Thailand's one-month Inter-bank rate. SMB_t is the difference between the monthly return of a portfolio of small stocks and the monthly return of portfolio of big stocks. HML_t is the difference between the monthly return of portfolio of high Book to Market stocks and the monthly return of portfolio of low Book to Market stocks. WML_t is the difference between the monthly return of portfolio of high return stocks during month *t-12* to *t-2* and the monthly return of portfolio of low return stocks during month *t-12* to *t-2*. $\varepsilon_{p,t}$ is a mean-zero error term. In Panel B, the CAPM models are estimated;

$$R_{p,t} - R_{f,t} = \alpha_0 + \beta_{1p}RMRF_t + \varepsilon_{p,t}$$

$R_{p,t}$ denotes the monthly rate of return of portfolio *p*. $R_{f,t}$ is the risk-free rate, Thailand's one-month Inter-bank rate. $RMRF_t$ is the monthly market return in excess of the Thailand's one-month Inter-bank rate. $\varepsilon_{p,t}$ is a mean-zero error term. The *t-statistics* are in the parentheses.

Panel A: The Four-Factor model

Portfolio	α_0	RmRf	SMB	HML	WML	Adj R^2
Lottery-like stocks	-0.0577 (-1.56)	0.0593 (1.05)	-0.0117 (-2.04)	0.0029 (0.92)	0.0017 (0.42)	13.97%
Nonlottery-like stock	0.0034 (0.98)	0.0173 (1.84)	-0.0061 (-2.49)	0.0012 (1.95)	0.0002 (0.09)	14.68%
Other stocks	0.0016 (0.25)	0.0390 (1.89)	-0.0077 (-2.17)	0.0019 (1.59)	0.0004 (0.18)	15.04%
Lottery – NonLottery	-0.0611 (-0.78)	0.0419 (1.69)	-0.0057 (-1.32)	0.0017 (0.71)	0.0018 (0.61)	7.96%
Lottery – Other stock	-0.0593 (-0.80)	0.0203 (1.11)	-0.0041 (-1.30)	0.0009 (0.60)	0.0012 (0.61)	5.42%

Panel B: The CAPM model

Portfolio	CAPM α	RmRf	Adj R^2
Lottery-like stocks	0.0061 (1.58)	0.9847 (6.36)	42.11%
Nonlottery-like stock	0.0112 (2.41)	0.7540 (8.03)	62.19%
Other stocks	0.0069 (1.01)	0.8419 (7.14)	55.16%
Lotttery-like – NonLottery-like	-0.0049 (-1.83)	0.2307 (5.15)	17.66%
Lottery-like – Other stocks	-0.0007 (-0.79)	0.1428 (4.01)	11.23%

Table 9

Lottery-like and Nonlottery-like Stock Performance of Different Investor Types

This table reports the portfolio returns of lottery-like and nonlottery-like stocks across different investor types. The sample period is from January 1999 to December 2008. The portfolio performances are measured as mean monthly portfolio return. Panel A shows the lottery-like stock portfolio performances. Panel B shows the nonlottery-like stock portfolio performances. The standard deviation of monthly portfolio returns also reported. The mean differences of portfolio performance between retail investor and institutional investor (foreign investor) are provided with *t-statistic*s in the parentheses.

Panel A : Lottery-like stock portfolio

	Monthly Mean Return	**Standard Deviation**
Retail investor	-0.0131	4.8105
Institutional investor	0.6064	1.9213
Foreign investor	0.7228	3.8445
Retail – Institution	-0.6195 (-3.73)	3.1192
Retail – Foreign	-0.7359 (-4.01)	3.9660

Panel B : Nonlottery-like stock portfolio

	Monthly Mean Return	**Standard Deviation**
Retail investor	0.1082	2.1409
Institutional investor	0.0803	1.0783
Foreign investor	0.1232	1.6522
Retail – Institution	0.0279 (0.73)	1.2159
Retail – Foreign	-0.0150 (-0.69)	0.6929

Table 10
Monday and Non-Monday Trading Activity

This table reports the Monday and Non-Monday trading activities of different investor types. The sample period is from January 1999 to December 2008. In Panel A, the difference in means of daily buy-initiated (sell-initiated) volume on Monday and Non-Monday of different stock-types are reported with the *t-statistics* in the parentheses below the mean differences. In Panel B, the daily net buy volumes on Monday and Non-Monday are presented in column A and B, respectively. The daily net buy is computed as; $NB_{ijt} = \sum_{n=1}^{N} B_{ijt,n} - \sum_{m=1}^{M} S_{ijt,m}$ where NB_{jit} is the net buy of stock *i* by investor *j* on day *t*. *B* is buy-initiated volume (value) of stock *i* by investor *j* on day *t*. *S* is sell-initiated volume (value) of stock *i* by investor *j* on day *t*. *M* is the total number of buy-initiated trades on day *t*. *N* is the total number of sell-initiated trades on day *t*. The means differences of net buy between Monday and Non-Monday are reported in the third column and the *t-statistics* are shown in the last column.

Panel A: Mean differences of Monday and Non-Monday buy and sell volume

	Retail	**Institution**	**Foreign**
Lottery-like stocks			
Buy Volume	-572,146 (-2.53)	3,016.7 (0.04)	-91,611 (-2.75)
Sell Volume	366,731 (1.97)	4,429.2 (0.07)	2,611 (0.07)
Non Lottery-like stocks			
Buy Volume	-61,960 (-3.72)	-20,618 (-2.54)	-47,912 (-2.97)
Sell Volume	31,767 (1.46)	7,618.2 (0.86)	-35,147 (-2.87)
Other stocks			
Buy Volume	-228,590 (-3.01)	-31,523 (-3.10)	-46,489 (-2.77)
Sell Volume	-137,248 (-2.07)	-18,501 (-1.76)	-68,597 (-3.56)

Panel B: Monday and Non-Monday net buy

	Monday (A)	**Non-Monday (B)**	**Mean Difference (A) – (B)**	*t-statistic*
Retail investor				
Lottery-like stocks	117,697	350,027	-233,329	(-3.09)
Nonlottery-like stocks	-20,296	10,217	-30,514	(-3.35)
Other stocks	24,755	117,114	-92,359	(-4.31)
Institutional investor				
Lottery-like stocks	-88,744	-88,297	446.31	(0.01)
Nonlottery-like stocks	-16,691	-6,710	9,981.2	(1.10)
Other stocks	-27,060	-13,795	-13,265	(1.19)
Foreign investor				
Lottery-like stocks	-11,793	-23,756	11,963	(-1.31)
Nonlottery-like stocks	-2,967	9,269.6	-12,237	(-2.78)
Other stocks	-12,405	9,620.9	-22,026	(-1.64)

Table 11
Investor Daily Trading Activity on Monday

The table reports the estimated coefficients of the following time-series regression;

$$ln(Total\ trading\ volume)_{j,t} = b_0 + b_1\ DummyMonday*DummyStockType_{j,t} + b_2\ DummyStockType_{j,t} + b_3 StockPrice_{j,t} + b_4 MktRet_{jt} + b_5\ MktRet_{j,t-1} + b_6\ lnSETVol_{j,t} + b_7\ lnSETVol_{j,t-1} + b_8 ln(Total\ trading\ volume)_{j,t-1} + \varepsilon_{j,t}$$

Total trading volume$_{j,t}$ is volume buy-initiated plus volume sell-initiated by investor *j* on day *t*. *DummyMonday*DummyStockType*$_{j,t}$ is dummy variable for different stock types which set equal to one if it is Monday and equal zero otherwise. *StockPrice*$_{j,t}$ is the price of stock *i* on day *t*. *MktRet*$_{j,t}$ is the stock market return on day *t*. *MktRet*$_{j,t-1}$ is the stock market return on day *t-1*. *SETVol*$_{j,t}$ is the market trading volume on day *t*. *SETVol*$_{j,t-1}$ is the market trading volume on day *t-1*. *Total trading volume*$_{j,t-1}$ is Total volume purchased and sold by investor *j* on day *t-1*. $\varepsilon_{j,t}$ is a mean-zero error term. The sample period is from January 1999 to December 2008. The White Heteroskedasticity Consistent Estimators for standards errors are employed. The *t-statistics* are presented in the parentheses below the estimated coefficients.

	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	$Adj.R^2$
Retail investor										
Lottery-like stocks	0.1528	-0.0405	0.0236	-0.0085	0.9025	0.9896	0.8499	-0.6605	0.8131	90.15%
	(2.13)	(-1.51)	(3.43)	(-5.27)	(3.06)	(3.02)	(6.67)	(-5.87)	(4.91)	
Nonlottery-like stocks	0.2851	-0.0406	-0.1389	-0.0057	1.0027	1.0182	0.8457	-0.6534	0.8010	90.21%
	(3.84)	(-1.52)	(-6.22)	(-6.86)	(3.00)	(3.12)	(9.54)	(-5.50)	(4.28)	
Other stocks	0.1440	-0.0337	0.0372	-0.0088	1.0282	0.9829	0.8512	-0.6595	-0.8115	90.15%
	(2.01)	(-1.43)	(3.06)	(-7.26)	(3.07)	(3.00)	(8.79)	(-5.80)	(-4.27)	
Institutional investor										
Lottery-like stocks	-0.6727	0.0801	-0.1762	-0.0070	-0.9092	-2.0976	0.7572	-0.2191	0.4553	57.99%
	(-4.32)	(1.53)	(-4.98)	(-7.09)	(-1.28)	(-3.04)	(4.59)	(-6.20)	(4.89)	
Nonlottery-like stocks	-0.4414	-0.1272	-0.1429	0.0005	-0.9759	-1.8693	0.7185	-0.2083	0.4577	57.59%
	(-2.77)	(-2.60)	(-3.19)	(0.39)	(-1.38)	(-2.70)	(4.47)	(-5.90)	(4.16)	
Other stocks	-0.6660	-0.0795	0.1429	-0.0031	-0.9632	-1.9491	0.7332	-0.2067	0.4544	58.03%
	(-4.28)	(-1.62)	(5.61)	(-4.33)	(-1.36)	(-2.82)	(4.93)	(-5.85)	(4.77)	
Foreign investor										
Lottery-like stocks	0.3757	-0.0286	-0.1612	-0.0043	-1.3082	-0.6993	0.7469	-0.3687	0.5741	72.54%
	(3.76)	(-0.87)	(-6.92)	(-6.45)	(-2.80)	(-1.53)	(5.48)	(-5.55)	(9.76)	
Nonlottery-like stocks	0.4967	-0.0636	-0.1103	0.0023	-1.3502	-0.6015	0.7308	-0.3786	0.5822	72.41%
	(4.79)	(-1.92)	(-3.63)	(2.64)	(-2.88)	(-1.31)	(5.71)	(-5.96)	(9.05)	
Other stocks	0.3664	-0.0472	0.1288	-0.0002	-1.3408	-0.6553	0.7384	-0.3714	0.5738	72.55%
	(3.66)	(-1.43)	(7.52)	(-0.58)	(-2.87)	(-1.43)	(5.15)	(-5.68)	(9.72)	

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Table 12
Buy-Sell Imbalance on Monday

The table reports the estimated coefficients of the following time-series regression;

$$BSI_{j,t} = b_0 + b_1\,DumMon{*}DumStockType_{j,t} + b_2 DumStockType_{j,t} + b_3 StockPrice_{j,t} + b_4 MktRet_{j,t} + b_5 MktRet_{j,t-1} + b_6 lnSETVol_{j,t} + b_7\,lnSETVol_{j,t-1} + b_8 BSI_{j,t-1} + \varepsilon_{j,t}$$

$BSI_{j,t}$ is Buy-Sell imbalance in volume of investor *j* on day *t*. $DummyMonday{*}DummyStockType_{j,t}$ is dummy variable for different stock types which set equal to one if it is Monday and equal zero otherwise. $StockPrice_{j,t}$ is the price of stock *i* on day *t*. $MktRet_{j,t}$ is the stock market return on day *t*. $MktRet_{j,t-1}$ is the stock market return on day *t-1*. $SETVol_{j,t}$ is the market trading volume on day *t*. $SETVol_{j,t-1}$ is the market trading volume on day *t-1*. $BSI_{j,t-1}$ is Buy-Sell imbalance in volume of investor *j* on day *t-1*. $\varepsilon_{j,t}$ is a mean-zero error term. The sample period is from January 1999 to December 2008. The White Heteroskedasticity Consistent Estimators for standards errors are employed. The *t-statistics* are presented in the parentheses below the estimated coefficients.

	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	$Adj.R^2$
Retail investor										
Lottery-like stocks	-0.1433	-0.0125	0.0008	-0.0005	0.9172	-1.2975	0.0274	-0.0161	0.0907	22.84%
	(-5.73)	(-1.82)	(2.19)	(-2.86)	(9.12)	(-7.19)	(4.76)	(-2.82)	(7.75)	
Nonlottery-like stocks	-0.1318	-0.0270	-0.0066	-0.0001	0.9123	-1.2885	0.0252	-0.0149	0.0918	22.95%
	(-5.11)	(-3.28)	(-0.88)	(-0.48)	(9.10)	(-7.13)	(4.37)	(-2.62)	(7.84)	
Other stocks	-0.1440	-0.0152	0.0078	-0.0004	0.9259	-1.2939	0.0271	-0.0159	0.0905	22.86%
	(-5.76)	(-1.84)	(1.84)	(-3.27)	(9.11)	(-7.16)	(4.69)	(-2.80)	(7.73)	
Institutional investor										
Lottery-like stocks	-0.2165	-0.0174	-0.0653	0.0008	0.8619	-1.5669	0.0428	-0.0307	0.2691	10.59%
	(-2.48)	(-0.59)	(-3.29)	(1.63)	(5.20)	(-4.00)	(2.19)	(-1.58)	(3.44)	
Nonlottery-like stocks	-0.2082	-0.0276	0.0310	0.0016	0.8620	-1.5592	0.0390	-0.0305	0.2715	10.45%
	(-2.32)	(-1.00)	(1.24)	(2.19)	(5.18)	(-3.98)	(1.98)	(-1.57)	(3.67)	
Other stocks	-0.2006	-0.0044	0.0267	0.0024	0.8573	-1.5724	0.0408	-0.0339	0.2710	10.47%
	(-2.30)	(-0.16)	(1.87)	(6.01)	(5.17)	(-4.01)	(2.08)	(-1.60)	(4.63)	
Foreign investor										
Lottery-like stocks	-0.5606	-0.0221	-0.0308	-0.0002	0.4301	0.5310	0.0337	0.0043	0.2364	21.94%
	(-2.49)	(-1.27)	(-2.54)	(-0.43)	(3.10)	(5.98)	(2.79)	(0.36)	(8.04)	
Nonlottery-like stocks	-0.5397	-0.0054	-0.0178	0.0011	0.4232	0.5148	0.0335	0.0015	0.2379	21.84%
	(-2.79)	(-0.31)	(-1.12)	(2.29)	(3.05)	(5.91)	(2.77)	(0.09)	(8.18)	
Other stocks	-0.5614	-0.0310	0.0289	0.0007	0.4218	0.5395	0.0314	0.0043	0.2371	21.94%
	(-2.50)	(-1.78)	(3.24)	(2.77)	(3.07)	(6.02)	(2.60)	(0.36)	(8.10)	

Table 13
Investor Daily Trading Activity in January

The table reports the estimated coefficients of the following time-series regression;

$$ln(Total\ trading\ volume)_{j,t} = b_0 + b_1\,DummyJan{*}DummyStockType_{j,t} + b_2\,DummyStockType_{j,t} + b_3StockPrice_{j,t} + b_4MktRet_{jt} + b_5\,MktRet_{j,t-1} + b_6\,lnSETVol_{j,t} + b_7\,lnSETVol_{j,t-1} + b_8ln(Total\ trading\ volume)_{j,t-1} + \varepsilon_{j,t}$$

Total trading volume$_{j,t}$ is volume buy-initiated plus volume sell-initiated by investor *j* on day *t*. *DummyJan*DummyStockType*$_{j,t}$ is dummy variable for different stock types which set equal to one if it is January and equal zero otherwise. *StockPrice*$_{j,t}$ is the price of stock *i* on day *t*. *MktRet*$_{j,t}$ is the stock market return on day *t*. *MktRet*$_{j,t-1}$ is the stock market return on day *t-1*. *SETVol*$_{j,t}$ is the market trading volume on day *t*. *SETVol*$_{j,t-1}$ is the market trading volume on day *t-1*. *Total trading volume*$_{j,t-1}$ is Total volume purchased and sold by investor *j* on day *t-1*. $\varepsilon_{j,t}$ is a mean-zero error term. The sample period is from January 1999 to December 2008. The White Heteroskedasticity Consistent Estimators for standards errors are employed. The *t-statistics* are presented in the parentheses below the estimated coefficients.

	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	$Adj.R^2$
Retail investor										
Lottery-like stocks	0.6981 (3.54)	-0.2513 (-3.99)	0.3145 (3.73)	-0.0062 (-2.19)	0.9174 (1.51)	0.1776 (2.68)	0.1145 (7.65)	0.1356 (5.43)	0.4564 (3.76)	72.34%
Nonlottery-like stocks	0.0726 (6.51)	0.0821 (1.51)	-1.6045 (-9.41)	-0.0045 (-5.78)	0.7708 (1.34)	0.1566 (2.58)	0.8638 (9.44)	0.2179 (0.43)	0.4573 (4.01)	70.91%
Other stocks	0.2114 (3.23)	0.0617 (0.76)	-0.1789 (-5.10)	-0.0079 (-4.08)	0.8790 (1.16)	0.0794 (2.80)	0.0765 (8.55)	0.1381 (4.01)	0.4663 (3.87)	60.98%
Institutional investor										
Lottery-like stocks	-0.9452 (-5.12)	-0.1659 (-2.06)	0.0281 (0.91)	0.0012 (7.78)	-1.6635 (-2.11)	-3.1235 (-4.23)	0.8569 (3.52)	0.0791 (2.05)	0.0176 (1.54)	47.43%
Nonlottery-like stocks	-0.9843 (-6.32)	-0.0512 (-0.65)	0.2934 (9.19)	-0.0078 (-1.10)	-1.6691 (-2.02)	-3.2785 (-4.24)	0.8570 (3.52)	0.0793 (1.99)	0.0132 (2.89)	46.96%
Other stocks	0.9158 (6.78)	-0.1521 (-2.34)	-0.1443 (-7.31)	0.0080 (4.53)	-2.0554 (-3.49)	-3.2116 (-4.34)	0.8272 (3.41)	0.0732 (0.78)	0.0386 (2.98)	62.54%
Foreign investor										
Lottery-like stocks	0.9661 (7.01)	0.0327 (0.54)	-0.1454 (-6.57)	0.0088 (4.89)	-2.1145 (-3.66)	-2.2342 (-3.65)	0.8446 (9.22)	0.0143 (0.69)	0.0124 (0.78)	59.65%
Nonlottery-like stocks	0.3781 (4.10)	0.0382 (1.23)	0.8276 (3.21)	0.0061 (1.98)	-2.1165 (-3.61)	-2.2344 (-3.67)	0.8448 (9.16)	0.0141 (0.57)	0.0745 (2.32)	59.99%
Other stocks	0.7165 (6.00)	0.0555 (0.93)	0.2856 (4.32)	-0.0045 (-2.83)	-2.1211 (-3.64)	-2.2345 (-3.61)	0.8441 (9.26)	0.0149 (0.49)	0.0799 (2.54)	59.54%

Table 14

Buy-Sell Imbalance in January

The table reports the estimated coefficients of the following time-series regression;

$$BSI_{j,t} = b_0 + b_1 DumJan*DumStockType_{j,t} + b_2 DumStockType_{j,t} + b_3 StockPrice_{j,t} + b_4 MktRet_{j,t} + b_5 MktRet_{j,t-1} + b_6 lnSETVol_{j,t} + b_7 lnSETVol_{j,t-1} + b_8 BSI_{j,t-1} + \varepsilon_{j,t}$$

$BSI_{j,t}$ is Buy-Sell imbalance in volume of investor *j* on day *t*. $DumJanaury*DumStockType_{j,t}$ is dummy variable for different stock types which set equal to one if it is January and equal zero otherwise. $StockPrice_{j,t}$ is the price of stock *i* on day *t*. $MktRet_{j,t}$ is the stock market return on day *t*. $MktRet_{j,t-1}$ is the stock market return on day *t-1*. $SETVol_{j,t}$ is the market trading volume on day *t*. $SETVol_{j,t-1}$ is the market trading volume on day *t-1*. $BSI_{j,t-1}$ is Buy-Sell imbalance in volume of investor *j* on day *t-1*. $\varepsilon_{j,t}$ is a mean-zero error term. The sample period is from January 1999 to December 2008. The White Heteroskedasticity Consistent Estimators for standards errors are employed. The *t-statistics* are presented in the parentheses below the estimated coefficients.

	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	$Adj.R^2$
Retail investor										
Lottery-like stocks	-0.1489 (-5.15)	-0.0164 (-1.19)	0.0112 (2.34)	-0.0007 (-2.16)	1.9176 (4.10)	-0.9167 (-7.12)	0.0280 (4.94)	-0.0681 (-3.01)	0.0876 (7.05)	22.96%
Nonlottery-like stocks	-0.1501 (-5.17)	-0.0490 (-2.18)	-0.0134 (-3.04)	-0.0002 (-0.81)	1.9178 (4.14)	-0.9168 (-7.11)	0.0283 (4.96)	-0.0688 (-3.02)	0.0855 (7.11)	22.99%
Other stocks	-0.1491 (-5.19)	-0.0010 (-0.08)	0.0063 (1.66)	-0.0011 (-3.71)	1.9171 (4.11)	-0.9146 (-7.12)	0.0281 (4.89)	-0.0689 (-3.05)	0.0861 (7.23)	22.92%
Institutional investor										
Lottery-like stocks	-0.2515 (-2.34)	0.0254 (0.21)	-0.0921 (-5.96)	0.0008 (1.21)	0.8771 (5.11)	-0.5741 (-4.04)	0.0349 (2.13)	-0.0419 (-1.43)	0.2943 (3.17)	11.85%
Nonlottery-like stocks	-0.2519 (-2.45)	-0.0581 (-1.24)	0.0746 (5.12)	0.0006 (2.93)	0.8772 (5.13)	-0.5744 (-4.07)	0.0345 (2.17)	-0.0417 (-1.44)	0.2942 (3.12)	11.63%
Other stocks	-0.2516 (-2.55)	-0.0365 (-0.76)	0.0123 (1.01)	0.0014 (6.98)	0.8779 (5.12)	-0.5749 (-4.08)	0.0348 (2.21)	-0.0420 (-1.47)	0.2951 (3.13)	10.34%
Foreign investor										
Lottery-like stocks	-0.5530 (-2.73)	0.0213 (0.89)	-0.0401 (-3.76)	-0.0001 (-0.18)	0.4304 (3.11)	0.4856 (5.22)	0.0361 (3.45)	0.0011 (0.11)	0.2099 (4.00)	22.56%
Nonlottery-like stocks	-0.5732 (-2.69)	0.0215 (0.98)	0.0084 (1.09)	0.0041 (2.65)	0.4301 (3.03)	0.4855 (5.28)	0.0359 (3.42)	0.0012 (0.13)	0.2089 (4.03)	22.25%
Other stocks	-0.5319 (-2.75)	0.0319 (1.26)	0.0141 (1.97)	0.0004 (2.12)	0.4308 (3.01)	0.4859 (5.26)	0.0356 (3.41)	0.0016 (0.11)	0.2096 (4.04)	22.65%

Table 15
Gambling Seasonality and the Market Anomaly

This table reports the estimated coefficients of the GJR-GARCH model. In this model, the autoregressive processes are used to correct the autocorrelation in stock returns. The sample period is from January 1999 to December 2008. Specifically, the following GARCH models are estimated;

$$R_{i,t} = \alpha_0 + \sum_{j=1}^{k} \phi_j R_{i,t-j} + \alpha_1 DummySeasonalVariable_{i,t} + \varepsilon_{i,t},$$

$$\varepsilon_{i,t} | \Omega_{i,t-1} \approx N(0, h_{i,t}),$$

$$h_{i,t} = \omega + \delta\varepsilon_{i,t-1}^2 + \gamma\varepsilon_{i,t-1}^2 D_{i,t-1} + \theta h_{i,t-1}$$

$R_{i,t}$ denotes the stock *i* daily return on day *t*. $R_{i,t-j}$ denotes the stock *i* daily return on day *t-j*. $DummySeasonalVariable_{i,t}$ is a dummy variable set equal to one if it is Monday in Panel A (January in Panel B) and equal zero otherwise. Ω_{t-1} is the information set at time *t-1*. D_{t-1} is a dummy variable that allow good news and bad news to have different impacts on the conditional variance. Where D_{t-1} equal to one if ε_{t-1} is less than zero (bad news), and D_{t-1} equals zero (good news) otherwise. The good news has only δ impact on volatility, while the bad news has a $\delta + \gamma$. The AIC and SIC are utilized for determining the optimal lags of returns. The *t-statistics* are reported in the parentheses below the estimated coefficients.

	α_0	$ø_1$	$ø_2$	$ø_3$	α_1	ω	δ	γ	θ
Panel A: Monday effect									
Lottery-like stocks	0.0013 (2.96)	0.0911 (3.75)	0.1006 (3.72)	0.0528 (1.89)	-0.0053 (-5.35)	0.00001 (4.28)	0.2337 (8.50)	-0.1306 (-5.02)	0.8168 (43.79)
Nonlottery-like stocks	0.0009 (3.77)	0.1037 (4.31)	0.0767 (2.84)	-0.0029 (-0.10)	-0.0033 (-6.18)	0.00006 (5.80)	0.1429 (6.81)	-0.0486 (-2.27)	0.8399 (43.43)
Other stocks	0.0012 (3.98)	0.0991 (3.88)	0.0995 (3.38)	0.0258 (0.83)	-0.0035 (-5.30)	0.00001 (5.33)	0.2836 (8.38)	-0.1709 (-5.43)	0.7815 (39.73)
Panel B: January effect									
	α_0	$ø_1$	$ø_2$	$ø_3$	α_1	ω	δ	γ	θ
Lottery-like stocks	0.0003 (0.49)	0.0889 (3.63)	0.0958 (3.54)	0.0499 (1.79)	0.0019 (1.36)	0.00002 (4.31)	0.2325 (8.45)	-0.1316 (-5.01)	0.8160 (43.33)
Nonlottery-like stocks	0.0002 (0.87)	0.0917 (3.78)	0.0756 (2.78)	-0.0037 (-0.13)	0.0012 (1.54)	0.00007 (5.91)	0.1394 (6.94)	-0.0577 (-2.83)	0.8451 (44.89)
Other stocks	0.0005 (1.75)	0.0949 (3.69)	0.0942 (3.20)	0.0156 (0.50)	0.0011 (1.11)	0.00001 (5.35)	0.2964 (8.54)	-0.1783 (-5.52)	0.7721 (38.24)

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Table 16
Buy-Sell Imbalance and the Day-of-the-Week Analysis

The table reports the estimated coefficients of the following time-series regression;

$$BSI_{j,t} = b_0 + b_1 DumWeekday*DumStockType_{j,t} + b_2 DumStockType_{j,t} + b_3 StockPrice_{j,t} + b_4 MktRet_{j,t} + b_5 MktRet_{j,t-1} + b_6 lnSETVol_{j,t} + b_7 lnSETVol_{j,t-1} + b_8 BSI_{j,t-1} + \varepsilon_{j,t}$$

$BSI_{j,t}$ is Buy-Sell imbalance in volume of investor *j* on day *t*. $DummyWeekday*DummyStockType_{j,t}$ is dummy variable for different stock types which set equal to one if it is Monday (Tuesday, Wednesday, Thursday, Friday) and equal zero otherwise. $StockPrice_{j,t}$ is the price of stock *i* on day *t*. $MktRet_{j,t}$ is the stock market return on day *t*. $MktRet_{j,t-1}$ is the stock market return on day *t-1*. $SETVol_{j,t}$ is he market trading volume on day *t*. $SETVol_{j,t-1}$ is the market trading volume on day *t-1*. $BSI_{j,t-1}$ is Buy-Sell imbalance in volume of investor *j* on day *t-1*. $\varepsilon_{j,t}$ is a mean-zero error term. The sample period is from January 1999 to December 2008. The White Heteroskedasticity Consistent Estimators for standards errors are employed. The *t-statistics* are presented in the parentheses below the estimated coefficients. For brevity, only *DummyWeekday coefficients* are shown, the other estimated coefficients are suppressed.

	Monday	Tuesday	Wednesday	Thursday	Friday
Retail investor					
Lottery-like stocks	-0.0057 (-2.51)	0.0116 (1.29)	0.0078 (1.14)	0.0084 (1.15)	-0.0003 (-0.04)
Nonlottery-like stocks	-0.0329 (-1.29)	0.0041 (0.39)	-0.0066 (-0.76)	-0.0201 (-2.61)	0.0019 (0.22)
Other stocks	-0.0071 (-1.11)	0.0119 (1.61)	0.0200 (1.72)	0.0039 (0.41)	0.0022 (0.09)
Institutional investor					
Lottery-like stocks	-0.0767 (-0.98)	-0.1191 (-3.91)	-0.0591 (-2.34)	-0.0271 (-0.81)	-0.0681 (-2.24)
Nonlottery-like stocks	0.0277 (1.19)	0.0249 (1.43)	0.0497 (2.01)	0.0548 (2.45)	0.0713 (2.72)
Other stocks	0.0053 (0.27)	-0.0191 (-0.51)	0.0141 (0.52)	0.0159 (0.52)	0.0177 (0.69)
Foreign investor					
Lottery-like stocks	-0.0521 (-0.48)	-0.0311 (-2.01)	-0.0059 (-0.47)	-0.0101 (-0.57)	-0.0253 (-1.49)
Nonlottery-like stocks	0.0047 (0.39)	0.0991 (0.69)	-0.0152 (-0.94)	0.0183 (0.85)	0.0221 (1.60)
Other stocks	-0.0108 (-0.67)	0.0121 (0.77)	0.0171 (1.12)	0.0144 (0.91)	0.0398 (2.29)

Table 17
Gambling Seasonality and the Day-of-the-Week Analysis

This table reports the estimated coefficients of the GJR-GARCH model. In this model, the autoregressive processes are used to correct the autocorrelation in stock returns. The sample period is from January 1999 to December 2008. Specifically, the following GARCH models are estimated;

$$R_{i,t} = \alpha_0 + \sum_{j=1}^{k} \phi_j R_{i,t-j} + \alpha_1 DummySeasonalVariable_{i,t} + \varepsilon_{i,t},$$
$$\varepsilon_{i,t} \big| \Omega_{i,t-1} \approx N(0, h_{i,t}),$$
$$h_{i,t} = \omega + \delta\varepsilon^2_{i,t-1} + \gamma\varepsilon^2_{i,t-1} D_{i,t-1} + \theta h_{i,t-1}$$

$R_{i,t}$ denotes the stock *i* daily return on day *t*. $R_{i,t-j}$ denotes the stock *i* daily return on day *t-j*. $DummySeasonalVariable_{i,t}$ is a dummy variable set equal to one if it is Monday (Tuesday, Wednesday, Thursday, and Friday for each model estimated) and equal zero otherwise. Ω_{t-1} is the information set at time *t-1*. D_{t-1} is a dummy variable that allow good news and bad news to have different impacts on the conditional variance. Where D_{t-1} equal to one if ε_{t-1} is less than zero (bad news), and D_{t-1} equals zero (good news) otherwise. The good news has only δ impact on volatility, while the bad news has a $\delta + \gamma$. The AIC and SIC are utilized for determining the optimal lags of returns. The *t-statistics* are reported in the parentheses below the estimated coefficients. For brevity, only α_1 of each model are shown and the other estimated coefficients are suppressed.

	Monday	***Tuesday***	***Wednesday***	***Thursday***	***Friday***
Lottery-like stocks	-0.0053 (-5.35)	0.00071 (1.11)	0.00059 (0.94)	-0.0004 (-0.62)	0.00099 (1.54)
Nonlottery-like stocks	-0.0033 (-6.18)	-0.00004 (-0.06)	0.00064 (0.95)	-0.0003 (-0.45)	0.00233 (3.43)
Other stocks	-0.0035 (-5.30)	0.00017 (0.25)	0.00158 (2.39)	0.00069 (1.04)	0.00229 (3.38)

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Table 18
Buy-Sell Imbalance and the Month-by-Month Analysis

The table reports the estimated coefficients of the following time-series regression;

$$BSI_{j,t} = b_0 + b_1\, DumMonth{*}DumStockType_{j,t} + b_2 DumStockType_{j,t} + b_3 StockPrice_{j,t} + b_4 MktRet_{j,t} + b_5 MktRet_{j,t-1} + b_6 lnSETVol_{j,t} + b_7\, lnSETVol_{j,t-1} + 8_7 BSI_{j,t-1} + \varepsilon_{j,t}$$

$BSI_{j,t}$ is Buy-Sell imbalance in volume of investor *j* on day *t*. $DumMonth{*}DumStockType_{j,t}$ is dummy variable for different stock types which set equal to one for each Month of the year (January, February, March, and so on) and equal zero otherwise. $StockPrice_{j,t}$ is the price of stock *i* on day *t*. $MktRet_{j,t}$ is the stock market return on day *t*. $MktRet_{j,t-1}$ is the stock market return on day *t-1*. $SETVol_{j,t}$ is the market trading volume on day *t*. $SETVol_{j,t-1}$ is the market trading volume on day *t-1*. $BSI_{j,t-1}$ is Buy-Sell imbalance in volume of investor *j* on day *t-1*. $\varepsilon_{j,t}$ is a mean-zero error term. The sample period is from January 1999 to December 2008. The White Heteroskedasticity Consistent Estimators for standards errors are employed. The *t-statistics* are presented in the parentheses below the estimated coefficients. For brevity, only b_1 for each month are shown, the other estimated coefficients are suppressed.

	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sep	Oct	Nov	Dec
Retail investor												
Lottery-like stocks	-0.0171	0.0094	-0.0182	0.0321	-0.0119	0.0216	-0.0233	-0.0489	0.0599	-0.0284	-0.0965	-0.0327
	(-1.39)	(0.81)	(-1.92)	(1.26)	(-0.42)	(2.34)	(-1.42)	(-1.92)	(1.40)	(-1.61)	(-1.34)	(-1.26)
Nonlottery-like stocks	0.0014	0.0029	0.0042	0.0212	0.0127	0.0034	0.0066	0.0024	0.0211	-0.0114	0.0156	-0.0117
	(0.11)	(0.38)	(1.03)	(0.07)	(0.53)	(0.32)	(0.71)	(0.59)	(0.09)	(0.71)	(0.91)	(-1.19)
Other stocks	0.0068	0.0043	-0.0177	0.0201	0.0174	-0.0084	0.0131	0.0151	0.0164	0.0931	0.0068	-0.0166
	(0.72)	(0.74)	(-1.71)	(1.18)	(0.53)	(-0.93)	(0.81)	(0.62)	(0.56)	(0.84)	(1.14)	(-1.79)
Institutional investor												
Lottery-like stocks	-0.1039	-0.0015	-0.0449	-0.0072	-0.0184	-0.0062	-0.0078	0.0021	-0.0775	-0.0101	-0.0089	0.0391
	(-0.51)	(-0.91)	(-0.69)	(-1.10)	(-0.19)	(-0.21)	(-1.41)	(0.18)	(-1.34)	(-0.55)	(-1.04)	(3.21)
Nonlottery-like stocks	0.0398	-0.0118	-0.0961	-0.0117	0.0127	-0.0113	-0.0120	-0.0780	0.0065	-0.0971	-0.0134	0.1251
	(1.51)	(-1.01)	(-1.12)	(-1.05)	(1.35)	(-0.39)	(-1.34)	(-1.13)	(1.01)	(-1.42)	(-1.23)	(1.61)
Other stocks	0.0511	0.0332	-0.0766	-0.0184	-0.0281	0.0101	-0.0011	-0.0542	-0.0089	0.1081	0.1211	0.0069
	(1.58)	(1.20)	(-1.05)	(-1.23)	(-1.03)	(1.21)	(-0.10)	(-1.51)	(-1.12)	(1.38)	(1.08)	(1.76)
Foreign investor												
Lottery-like stocks	-0.0139	-0.0274	-0.0254	0.0019	-0.0078	-0.0024	-0.0017	-0.0077	-0.0021	-0.0059	-0.0081	0.0013
	(-0.93)	(-0.43)	(-0.91)	(0.13)	(-0.25)	(-0.31)	(-0.55)	(-1.62)	(0.12)	(-0.34)	(-0.35)	(0.15)
Nonlottery-like stocks	0.0185	-0.0491	0.0192	-0.0932	0.0763	-0.0004	-0.0114	-0.0131	-0.0218	0.0813	0.1102	-0.0114
	(1.28)	(-1.18)	(1.24)	(-1.32)	(1.10)	(-0.09)	(-1.11)	(-1.04)	(-0.64)	(1.03)	(1.12)	(-0.77)
Other stocks	0.0242	-0.0377	-0.0781	-0.0061	0.0535	0.0125	0.0242	-0.0398	-0.0221	0.0409	0.2297	-0.0018
	(1.61)	(-1.32)	(-1.04)	(-1.09)	(1.47)	(1.81)	(1.10)	(1.52)	(-0.45)	(1.08)	(1.53)	(-0.18)

Table 19
Gambling Seasonality and the Month-by-Month Analysis

This table reports the estimated coefficients of the GJR-GARCH model. In this model, the autoregressive processes are used to correct the autocorrelation in stock returns. The sample period is from January 1999 to December 2008. Specifically, the following GARCH models are estimated;

$$R_{i,t} = \alpha_0 + \sum_{j=1}^{k} \phi_j R_{i,t-j} + \alpha_1 DummySeasonalVariable_{i,t} + \varepsilon_{i,t},$$

$$\varepsilon_{i,t} \left| \Omega_{i,t-1} \approx N\left(0, h_{i,t}\right),\right.$$

$$h_{i,t} = \omega + \delta\varepsilon_{i,t-1}^2 + \gamma\varepsilon_{i,t-1}^2 D_{i,t-1} + \theta h_{i,t-1}$$

$R_{i,t}$ denotes the stock *i* daily return on day *t*. $R_{i,t-j}$ denotes the stock *i* daily return on day *t-j*. In Panel A, $DummySeasonalVariable_{i,t}$ is a dummy variable set equal to one if it is January (Febuary, March, and so on for each model estimated) and equal zero otherwise. In Panel B, $DummySeasonalVariable_{j,t}$, *JAN (NonJan)* is equals to one for January (Non January) and equals zero otherwise. Ω_{t-1} is the information set at time *t-1*. D_{t-1} is a dummy variable that allow good news and bad news to have different impacts on the conditional variance. Where D_{t-1} equal to one if ε_{t-1} is less than zero (bad news), and D_{t-1} equals zero (good news) otherwise. The good news has only δ impact on volatility, while the bad news has a $\delta + \gamma$. The AIC and SIC are utilized for determining the optimal lags of returns. The *t-statistics* are reported in the parentheses below the estimated coefficients. For brevity, only α_1 of each month are shown and the other estimated coefficients are suppressed in Panel A.

Panel A: Month-by-Month analysis

α_1	*Jan*	*Feb*	*Mar*	*Apr*	*May*	*Jun*	*Jul*	*Aug*	*Sep*	*Oct*	*Nov*	*Dec*
Lottery-like	0.0019 (1.36)	-0.0003 (-0.29)	-0.0029 (-3.37)	-0.0003 (-0.34)	-0.0007 (-0.73)	0.0034 (3.27)	-0.0019 (-1.84)	-0.0022 (-2.30)	-0.0004 (-0.46)	-0.0021 (-2.27)	-0.0017 (-1.86)	0.0027 (2.78)
Nonlottery-like	0.0012 (1.54)	0.0074 (0.68)	-0.0013 (-1.33)	-0.0034 (-0.36)	0.0069 (0.64)	0.0013 (1.09)	-0.0004 (-0.04)	-0.0003 (-0.30)	0.0003 (0.26)	0.0002 (0.19)	0.0001 (0.01)	0.00007 (0.07)
Other stocks	0.0011 (1.11)	0.0009 (0.88)	-0.0015 (-1.55)	0.0001 (0.11)	0.0004 (0.36)	0.0023 (2.01)	0.0001 (0.05)	-0.0001 (-0.10)	0.0005 (0.53)	0.0004 (0.41)	0.0002 (0.19)	0.0024 (2.21)

Panel B: January and Non-January analysis

	α_0	$\emptyset_1$	$\emptyset_2$	$\emptyset_3$	*Jan*	*NonJan*	ω	δ	γ	θ
Lottery-like	0.0011 (4.96)	0.1059 (8.33)	0.0783 (6.23)	0.0477 (3.88)	0.0006 (0.65)	-0.0010 (-2.82)	0.00004 (6.65)	0.1154 (3.80)	-0.0581 (-7.89)	0.9056 (15.67)
Nonlottery-like	0.0007 (3.29)	0.1058 (8.33)	0.0779 (6.21)	0.04767 (3.87)	0.0014 (0.98)	0.0001 (0.32)	0.00003 (6.66)	0.1124 (4.20)	-0.0545 (-7.88)	0.9067 (15.07)
Other stocks	0.0005 (2.51)	0.1062 (8.36)	0.0784 (6.25)	0.04787 (3.89)	0.0015 (1.11)	0.0007 (1.58)	0.00004 (6.63)	0.1139 (3.87)	-0.0564 (-7.86)	0.9061 (14.74)

Table 20
June and Non-June Trading Activity

This table reports the June and Non-June trading activities of different investor types. The sample period is from January 1999 to December 2008. In Panel A, the difference in means of daily buy-initiated (sell-initiated) volume on June and Non-June of different stock-types are reported with the *t-statistics* in the parentheses below the mean differences. In Panel B, the daily net buy volumes on June and Non-June are presented in column A and B, respectively. The daily net buy is computed as; $NB_{ijt} = \sum_{n=1}^{N} B_{ijt,n} - \sum_{m=1}^{M} S_{ijt,m}$ where NB_{jit} is the net buy of stock *i* by investor *j* on day *t*. *B* is buy-initiated volume (value) of stock *i* by investor *j* on day *t*. *S* is sell-initiated volume (value) of stock *i* by investor *j* on day *t*. *M* is the total number of buy-initiated trades on day *t*. *N* is the total number of sell-initiated trades on day *t*. The means differences of net buy between June and Non-June are reported in the third column and the *t-statistics* are shown in the last column.

Panel A: Mean differences of June and Non-June buy and sell volume

	Retail	Institution	Foreign
Lottery-like stocks			
Buy Volume	549E3 (1.98)	-175,158 (-4.12)	-1,322.9 (-0.03)
Sell Volume	322E3 (1.07)	219E3 (1.56)	-11,137 (-0.22)
Nonlottery-like stocks			
Buy Volume	-50,119 (-2.28)	-30,222 (-2.65)	-23,078 (-1.21)
Sell Volume	-67,403 (-3.24)	-4,080.6 (-0.32)	-24,154 (-1.42)
Other stocks			
Buy Volume	45,480 (0.37)	26,096 (0.25)	9,860.2 (0.35)
Sell Volume	15,679 (0.15)	-22,458 (-0.26)	-45,703 (-1.92)

Panel B: June and Non-June net buy

	June (A)	Non-June (B)	Mean Difference (A) – (B)	*t-statistic*
Retail investor				
Lottery-like stocks	464,922	291,518	173E3	(2.51)
Nonlottery-like stocks	20,403	2,991.1	17,412	(1.37)
Other stocks	72,414	102,298	-29,884	(-0.82)
Institutional investor				
Lottery-like stocks	-54,853	-49,483	-5,336	(-1.49)
Nonlottery-like stocks	-33,582	-6,215	-27,367	(-2.02)
Other stocks	-21,960	-15,757	-6,202.6	(-0.44)
Foreign investor				
Lottery-like stocks	-32,129	-42,218	10,089	(0.23)
Nonlottery-like stocks	8,301.9	6,843.7	1,458	(0.07)
Other stocks	28,203	9,421.2	18,782	(1.52)

Table 21
Investor Daily Trading Activity in June

The table reports the estimated coefficients of the following time-series regression;

$$ln(Total\ trading\ volume)_{j,t} = b_0 + b_1\ DummyJune{*}DummyStockType_{j,t} + b_2\ DummyStockType_{j,t} + b_3 StockPrice_{j,t} + b_4 MktRet_{jt} + b_5\ MktRet_{,t-1} + b_6\ lnSETVol_{j,t} + b_7\ lnSETVol_{j,t-1} + b_8 ln(Total\ trading\ volume)_{j,t-1} + \varepsilon_{j,t}$$

Total trading volume$_{j,t}$ is volume buy-initiated plus volume sell-initiated by investor *j* on day *t*. *DummyJune*DummyStockType*$_{j,t}$ is dummy variable for different stock types which set equal to one if it is June and equal zero otherwise. *StockPrice*$_{j,t}$ is the price of stock *i* on day *t*. *MktRet*$_{j,t}$ is the stock market return on day *t*. *MktRet*$_{j,t-1}$ is the stock market return on day *t-1*. *SETVol*$_{j,t}$ is the market trading volume on day *t*. *SETVol*$_{j,t-1}$ is the market trading volume on day *t-1*. *Total trading volume*$_{j,t-1}$ is Total volume purchased and sold by investor *j* on day *t-1*. $\varepsilon_{j,t}$ is a mean-zero error term. The sample period is from January 1999 to December 2008. The White Heteroskedasticity Consistent Estimators for standards errors are employed. The *t-statistics* are presented in the parentheses.

	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	$Adj.R^2$
Retail investor										
Lottery-like stocks	0.9832 (2.14)	0.3391 (3.18)	0.7894 (6.18)	-0.0076 (-4.71)	0.8332 (1.42)	0.7654 (2.89)	0.9231 (6.37)	0.0189 (2.14)	0.4184 (4.32)	75.32%
Nonlottery-like stocks	1.0024 (3.12)	-0.1922 (-3.05)	1.5883 (-8.23)	-0.0054 (-5.69)	0.7991 (1.39)	0.8764 (2.88)	0.9349 (6.39)	0.0134 (0.87)	0.4054 (4.89)	72.33%
Other stocks	0.9961 (2.92)	-0.1389 (-1.68)	-0.1901 (-4.28)	-0.0028 (-6.24)	0.8643 (1.22)	0.7964 (2.83)	0.9399 (6.31)	0.0183 (2.26)	0.4113 (4.02)	65.17%
Institutional investor										
Lottery-like stocks	-1.1287 (-5.31)	0.3128 (4.12)	-0.0183 (-0.45)	-0.0065 (-6.04)	-1.7068 (-2.11)	-0.9873 (-4.04)	0.8563 (6.53)	0.0867 (2.21)	0.0154 (1.23)	48.16%
Nonlottery-like stocks	-1.8712 (-4.32)	-0.4732 (-1.22)	0.8783 (2.45)	0.0006 (0.42)	-1.6996 (-2.12)	-0.9767 (-4.03)	0.8569 (6.51)	0.0891 (1.29)	0.0441 (2.02)	48.34%
Other stocks	-1.3234 (-6.19)	-0.0698 (-0.43)	0.2391 (3.01)	-0.0054 (-3.21)	-1.6752 (-2.03)	-0.9465 (-4.05)	0.8562 (6.55)	0.0763 (1.94)	0.0345 (2.42)	47.19%
Foreign investor										
Lottery-like stocks	0.9341 (5.32)	0.1998 (1.43)	-0.1894 (-8.02)	-0.0032 (-5.64)	-0.0727 (-3.19)	-0.8763 (-3.13)	0.0389 (4.53)	0.0131 (0.32)	0.0326 (2.43)	23.25%
Nonlottery-like stocks	-0.5621 (-6.01)	0.0013 (0.03)	0.0218 (1.24)	0.0013 (3.51)	0.4910 (3.16)	-0.8867 (-3.89)	0.0388 (4.55.)	0.0127 (0.12)	0.2369 (2.19)	23.69%
Other stocks	-0.5672 (-6.33)	0.0352 (2.37)	0.0152 (1.93)	-0.0011 (-0.79)	0.4367 (3.18)	-0.8801 (-3.76)	0.0381 (4.59)	0.0013 (0.09)	0.2368 (2.14)	23.63%

Table 22
Buy-Sell Imbalance in June

The table reports the estimated coefficients of the following time-series regression;

$$BSI_{j,t} = b_0 + b_1\, DumJune{*}DumStockType_{j,t} + b_2 DummyStockType_{j,t} + b_3 StockPrice_{j,t} + b_4 MktRet_{j,t} + b_5 MktRet_{j,t-1} + b_6 lnSETVol_{j,t} + b_7\, lnSETVol_{j,t-1} + b_8 BSI_{j,t-1} + \varepsilon_{j,t}$$

$BSI_{j,t}$ is Buy-Sell imbalance in volume of investor *j* on day *t*. $DummyJune{*}DummyStockType_{j,t}$ is dummy variable for different stock types which set equal to one if it is June and equal zero otherwise. $StockPrice_{j,t}$ is the price of stock *i* on day *t*. $MktRet_{j,t}$ is the stock market return on day *t*. $MktRet_{j,t-1}$ is the stock market return on day *t-1*. $SETVol_{j,t}$ is the market trading volume on day *t*. $SETVol_{j,t-1}$ is the market trading volume on day *t-1*. $BSI_{j,t-1}$ is Buy-Sell imbalance in volume of investor *j* on day *t-1*. $\varepsilon_{j,t}$ is a mean-zero error term. The sample period is from January 1999 to December 2008. The White Heteroskedasticity Consistent Estimators for standards errors are employed. The *t-statistics* are presented in the parentheses below the estimated coefficients.

	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	$Adj.R^2$
Retail investor										
Lottery-like stocks	-0.1374 (-5.09)	0.0249 (2.19)	0.0078 (1.23)	-0.0006 (-2.46)	0.9135 (4.08)	-0.4192 (-6.58)	0.0283 (4.94)	-0.0179 (-3.20)	0.0914 (7.03)	22.78%
Nonlottery-like stocks	-0.1299 (-5.01)	0.0197 (1.60)	-0.0178 (-4.02)	-0.0005 (-0.97)	0.9134 (4.17)	-0.4196 (-6.51)	0.0285 (4.89)	-0.0182 (-3.21)	0.0911 (7.03)	22.83%
Other stocks	-0.1374 (-5.06)	-0.0139 (-1.07)	0.0089 (1.93)	-0.0029 (-4.64)	0.9142 (4.14)	-0.4189 (-6.54)	0.0280 (4.91)	-0.0178 (-3.14)	0.0915 (7.02)	22.69%
Institutional investor										
Lottery-like stocks	-0.2498 (-2.42)	0.0073 (0.13)	-0.0899 (-5.98)	0.0019 (1.13)	0.4329 (5.11)	-0.5745 (-8.01)	0.0064 (2.18)	-0.0011 (-1.51)	0.3253 (8.43)	11.26%
Nonlottery-like stocks	-0.2511 (-2.43)	-0.1076 (-2.45)	0.0815 (5.93)	0.0007 (2.34)	0.4324 (5.10)	-0.5746 (-8.04)	0.0063 (2.19)	-0.0012 (-1.59)	0.3481 (8.54)	11.12%
Other stocks	-0.2489 (-2.31)	-0.0123 (-0.28)	0.0819 (0.97)	0.0017 (6.01)	0.4387 (5.14)	-0.5742 (-8.06)	0.0067 (2.16)	-0.0015 (-1.52)	0.3511 (8.59)	10.34%
Foreign investor										
Lottery-like stocks	-0.5643 (-4.23)	0.0165 (0.47)	-0.0311 (-3.37)	-0.0018 (-0.97)	0.9724 (3.13)	0.1371 (5.89)	0.0032 (2.94)	0.0016 (0.13)	0.2114 (7.71)	22.85%
Nonlottery-like stocks	-0.5711 (-4.25)	0.0019 (0.12)	0.0152 (1.24)	0.0013 (3.45)	0.9729 (3.17)	0.1379 (5.81)	0.0035 (3.01)	0.0014 (0.12)	0.2116 (7.74)	22.71%
Other stocks	-0.5719 (-4.19)	0.0074 (1.49)	0.0148 (1.93)	0.0002 (2.67)	0.9727 (3.15)	0.1366 (5.85)	0.0038 (2.94)	0.0117 (0.09)	0.2112 (7.68)	22.78%

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Table 23
December and Non-December Trading Activity

This table reports the December and Non- December trading activities of different investor types. The sample period is from January 1999 to December 2008. In Panel A, the difference in means of daily buy-initiated (sell-initiated) volume on December and Non- December of different stock-types are reported with the *t-statistics* in the parentheses below the mean differences. In Panel B, the daily net buy volumes on December and Non- December are presented in column A and B, respectively. The daily net buy is computed as; $NB_{ijt} = \sum_{n=1}^{N} B_{ijt,n} - \sum_{m=1}^{M} S_{ijt,m}$ where NB_{jit} is the net buy of stock *i* by investor *j* on day *t*. *B* is buy-initiated volume (value) of stock *i* by investor *j* on day *t*. *S* is sell-initiated volume (value) of stock *i* by investor *j* on day *t*. *M* is the total number of buy-initiated trades on day *t*. *N* is the total number of sell-initiated trades on day *t*. The means differences of net buy between December and Non- December are reported in the third column and the *t-statistics* are shown in the last column.

Panel A: Mean differences of December and Non-December buy and sell volume

	Retail	Institution	Foreign
Lottery-like stocks			
Buy Volume	252E3 (0.68)	493E3 (6.45)	-82,087 (-2.14)
Sell Volume	134E3 (0.43)	4,511 (0.06)	-63,764 (-1.43)
Nonlottery-like stocks			
Buy Volume	-101,316 (-5.65)	15,724 (1.47)	-24,748 (-0.96)
Sell Volume	-82,983 (-4.73)	-5,016.4 (-0.37)	-23,766 (-1.25)
Other stocks			
Buy Volume	26,096 (0.25)	40,746 (2.24)	-18,614 (-0.63)
Sell Volume	22,458 (0.26)	8,304 (0.50)	6,066 (0.17)

Panel B: December and Non-December net buy

	December (A)	Non-December (B)	Mean Difference (A) – (B)	*t-statistic*
Retail investor				
Lottery-like stocks	420,138	296,640	123E3	(0.91)
Nonlottery-like stocks	-12,444	5,920.4	-18,365	(-1.39)
Other stocks	144,487	95,933	48,554	(1.44)
Institutional investor				
Lottery-like stocks	358,194	-13E4	488E3	(4.42)
Nonlottery-like stocks	10,452	-10,200	20,651	(1.58)
Other stocks	13,489	-18,813	32,302	(1.75)
Foreign investor				
Lottery-like stocks	-58,035	-39,929	-18,106	(-0.41)
Nonlottery-like stocks	6,356.7	7,020.4	-663.75	(-0.03)
Other stocks	-17,015	7,394.6	-24,409	(-0.99)

Table 24
Investor daily trading activity in December

The table reports the estimated coefficients of the following time-series regression;

$$\ln(\text{Total trading volume})_{j,t} = b_0 + b_1\, DummyDecember{*}DummyStockType_{j,t} + b_2\, DummyStockType_{j,t} + b_3 StockPrice_{j,t}$$
$$+ b_3 MktRet_{jt} + b_4\, MktRet_{j,t-1} + b_5 \ln SETVol_{j,t} + b_6 \ln SETVol_{j,t-1} + b_7 \ln(\text{Total trading volume})_{j,t-1} + \varepsilon_{j,t}$$

Total trading volume$_{j,t}$ is volume buy-initiated plus volume sell-initiated by investor *j* on day *t*. *DummyDecember*DummyStockType*$_{j,t}$ is dummy variable for different stock types which set equal to one if it is December and equal zero otherwise. *StockPrice*$_{j,t}$ is the price of stock *i* on day *t*. *MktRet*$_{j,t}$ is the stock market return on day *t*. *MktRet*$_{j,t-1}$ is the stock market return on day *t-1*. *SETVol*$_{j,t}$ is the market trading volume on day *t*. *SETVol*$_{j,t-1}$ is the market trading volume on day *t-1*. *Total trading volume*$_{j,t-1}$ is Total volume purchased and sold by investor *j* on day *t-1*. $\varepsilon_{j,t}$ is a mean-zero error term. The sample period is from January 1999 to December 2008. The White Heteroskedasticity Consistent Estimators for standards errors are employed. The *t-statistics* are presented in the parentheses.

	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	$Adj.R^2$
Retail investor										
Lottery-like stocks	0.7623	0.2378	0.7831	-0.0089	0.8645	0.1823	0.8342	0.1433	0.3194	81.23%
	(2.67)	(1.53)	(3.21)	(-3.89)	(1.23)	(2.97)	(6.32)	(5.34)	(3.17)	
Nonlottery-like stocks	0.8453	-0.2398	-0.7321	-0.0023	0.8732	0.7834	0.8129	0.1398	0.1428	75.65%
	(3.53)	(-3.91)	(-8.03)	(-5.12)	(1.18)	(2.12)	(6.43)	(5.49)	(4.01)	
Other stocks	0.8532	-0.2841	-0.1873	-0.0054	0.8761	0.8945	0.7632	0.1928	0.2643	63.43%
	(2.94)	(-2.72)	(-4.23)	(-6.49)	(1.02)	(2.03)	(6.19)	(5.65)	(4.43)	
Institutional investor										
Lottery-like stocks	-0.8114	0.3934	-0.0149	-0.0078	-0.6782	-0.5643	0.8524	0.0781	0.0198	47.13%
	(-4.16)	(3.12)	(-0.23)	(-6.23)	(-2.01)	(-4.12)	(4.52)	(2.02)	(1.21)	
Nonlottery-like stocks	-0.8737	0.0137	-0.9247	-0.0013	-0.6348	-0.5648	0.8489	0.0775	0.0193	47.32%
	(-3.23)	(0.14)	(-7.02)	(-0.97)	(-2.12)	(-4.16)	(4.54)	(2.01)	(1.63)	
Other stocks	-0.8478	0.0415	0.2381	-0.0039	-0.7002	-0.5701	0.8508	0.0748	0.0324	47.21%
	(-4.34)	(0.12)	(6.29)	(-3.98)	(-2.21)	(-4.13)	(4.51)	(1.95)	(2.61)	
Foreign investor										
Lottery-like stocks	0.8389	-0.0036	-0.1812	-0.0029	-0.4602	-0.7432	0.8369	0.0188	0.0144	60.14%
	(5.05)	(-0.03)	(-6.13)	(-5.42)	(-3.12)	(-2.97)	(9.18)	(0.34)	(2.34)	
Nonlottery-like stocks	0.8550	-0.2191	-0.1398	0.0032	-0.4621	-0.7630	0.8373	0.0151	0.0121	60.24%
	(5.39)	(-3.02)	(-5.13)	(4.19)	(-3.15)	(-2.91)	(9.23)	(0.69)	(0.21)	
Other stocks	0.8941	-0.1129	0.2239	0.0019	-0.4611	-0.7431	0.8371	0.0178	0.0425	60.43%
	(5.34)	(-2.27)	(4.78)	(1.04)	(-3.18)	(-2.93)	(9.24)	(0.76)	(2.19)	

Table 25
Buy-Sell Imbalance in December

The table reports the estimated coefficients of the following time-series regression;

$$BSI_{j,t} = b_0 + b_1\, DummyDec{*}DumStockType_{j,t} + b_2 DumStockType_{j,t} + b_3 StockPrice_{j,t} + b_4 MktRet_{j,t} + b_5 MktRet_{j,t-1} + b_6 lnSETVol_{j,t} + b_7\, lnSETVol_{j,t-1} + b_8 BSI_{j,t-1} + \varepsilon_{j,t}$$

$BSI_{j,t}$ is Buy-Sell imbalance in volume of investor *j* on day *t*. $DummyDecember{*}DummyStockType_{j,t}$ is dummy variable for different stock types which set equal to one if it is December and equal zero otherwise. $StockPrice_{j,t}$ is the price of stock *i* on day *t*. $MktRet_{j,t}$ is the stock market return on day *t*. $MktRet_{j,t-1}$ is the stock market return on day *t-1*. $SETVol_{j,t}$ is the market trading volume on day *t*. $SETVol_{j,t-1}$ is the market trading volume on day *t-1*. $BSI_{j,t-1}$ is Buy-Sell imbalance in volume of investor *j* on day *t-1*. $\varepsilon_{j,t}$ is a mean-zero error term. The sample period is from January 1999 to December 2008. The White Heteroskedasticity Consistent Estimators for standards errors are employed. The *t-statistics* are presented in the parentheses below the estimated coefficients.

	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	$Adj.R^2$
Retail investor										
Lottery-like stocks	-0.1481 (-3.21)	-0.0179 (-1.23)	0.0072 (2.31)	-0.0004 (-2.83)	0.9255 (9.11)	-0.8618 (-7.01)	0.0254 (4.81)	-0.0169 (-3.56)	0.0952 (6.54)	24.19%
Nonlottery-like stocks	-0.1497 (-3.42)	-0.0512 (-3.89)	-0.0118 (-2.63)	-0.0012 (-0.32)	0.9256 (9.24)	-0.8722 (-7.03)	0.0283 (4.82)	-0.0172 (-3.52)	0.0898 (6.48)	23.99%
Other stocks	-0.1398 (-3.31)	0.0049 (0.21)	0.0034 (1.55)	-0.0014 (-3.21)	0.9269 (9.17)	-0.8785 (-7.03)	0.0265 (4.87)	-0.0178 (-3.53)	0.0953 (6.52)	24.01%
Institutional investor										
Lottery-like stocks	-0.2264 (-2.01)	0.1467 (2.57)	-0.1031 (-6.84)	0.0013 (1.09)	0.8412 (5.06)	-0.6134 (-3.54)	0.0452 (2.05)	-0.0319 (-1.65)	0.2532 (3.21)	12.16%
Nonlottery-like stocks	-0.2681 (-2.12)	0.1185 (2.87)	0.0639 (4.32)	0.0004 (2.21)	0.8532 (5.02)	-0.5864 (-3.52)	0.0459 (2.09)	-0.0323 (-1.66)	0.2872 (3.38)	12.24%
Other stocks	-0.2790 (-2.34)	0.0560 (1.32)	0.0011 (0.32)	0.0011 (5.67)	0.8874 (5.18)	-0.6528 (-3.67)	0.0451 (2.01)	-0.0324 (-1.65)	0.2219 (3.47)	11.97%
Foreign investor										
Lottery-like stocks	-0.5154 (-4.19)	0.0032 (0.15)	-0.0321 (-3.21)	-0.0021 (-0.43)	0.4349 (2.97)	0.5092 (5.71)	0.0317 (3.01)	0.0014 (0.13)	0.2411 (6.67)	22.34%
Nonlottery-like stocks	-0.5621 (-2.42)	-0.0228 (-1.15)	0.0129 (1.59)	0.0017 (3.23)	0.4345 (2.96)	0.5089 (5.73)	0.0313 (2.97)	0.0012 (0.18)	0.2398 (6.23)	22.21%
Other stocks	-0.5543 (-2.28)	-0.0398 (-1.21)	0.0219 (2.54)	0.0001 (3.17)	0.4343 (2.91)	0.5071 (5.78)	0.0312 (2.95)	0.0016 (0.15)	0.2312 (6.12)	21.99%

Table 26
Investor Trading Activity and the Market Extremely Moves

The table reports the estimated coefficients of the following time-series regression;

$$ln(Total\ trading\ volume)_{j,t} = b_0 + b_1\ DummyMktMove*DummyStockType_{j,t} + b_2\ DummyStockType_{j,t} + b_3 StockPrice_{j,t} + b_4 MktRet_{jt} + b_5\ MktRet_{j,t-1} + b_6\ lnSETVol_{j,t} + b_7\ lnSETVol_{j,t-1} + b_8 ln(Total\ trading\ volume)_{j,t-1} + \varepsilon_{j,t}$$

Total trading volume$_{j,t}$ is volume buy-initiated plus volume sell-initiated by investor *j* on day *t*. *DummyMktMove*DummyStockType*$_{j,t}$ is dummy variable for different stock types which set equal to one if it is the trading day that the market increases (decreases in Panel B) more than 3% and equal zero otherwise. *StockPrice*$_{j,t}$ is the price of stock *i* on day *t*. *MktRet*$_{j,t}$ is the stock market return on day *t*. *MktRet*$_{j,t-1}$ is the stock market return on day *t-1*. *SETVol*$_{j,t}$ is the market trading volume on day *t*. *SETVol*$_{j,t-1}$ is the market trading volume on day *t-1*. *Total trading volume*$_{j,t-1}$ is Total volume purchased and sold by investor *j* on day *t-1*. $\varepsilon_{j,t}$ is a mean-zero error term. The sample period is from January 1999 to December 2008. The White Heteroskedasticity Consistent Estimators for standards errors are employed. The *t-statistics* are presented in the parentheses below the estimated coefficients.

Panel A: Mkt increase	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	$Adj.R^2$
Retail investor										
Lottery-like stocks	0.7921	-0.5278	0.3303	-0.0009	0.5642	0.1178	0.8943	0.1556	-0.4189	70.17%
	(3.43)	(-5.09)	(4.43)	(-2.76)	(2.32)	(3.16)	(7.12)	(5.01)	(-5.34)	
Nonlottery-like stocks	0.0376	0.1823	-1.6112	-0.0014	0.5452	0.4468	0.8498	0.0199	0.0456	72.13%
	(5.98)	(1.82)	(-7.23)	(-4.15)	(0.34)	(2.43)	(8.12)	(0.45)	(4.23)	
Other stocks	0.1324	0.3078	-0.1867	-0.0041	0.4744	0.1178	0.0748	-0.1523	-0.3633	54.45%
	(3.12)	(2.13)	(-5.11)	(-4.98)	(0.23)	(2.84)	(8.03)	(4.01)	(-4.13)	
Institutional investor										
Lottery-like stocks	-0.0343	-0.0943	0,0115	-0.0021	-0.6189	-0.2892	0.8555	-0.0845	0.0145	46.34%
	(-5.15)	(-0.03)	(0.21)	(-6.02)	(-2.01)	(-4.02)	(3.12)	(-2.01)	(1.32)	
Nonlottery-like stocks	-0.8621	0.0894	-0.2887	-0.0002	0.6194	-0.2823	0.8559	-0.0718	0.0181	47.98%
	(-4.23)	(1.65)	(-3.12)	(-0.45)	(-2.01)	(-4.04)	(3.16)	(-2.03)	(1.65)	
Other stocks	-0.1887	0.1623	0.2743	-0.0028	0.6132	-0.2796	0.8565	0.0723	0.0153	48.06%
	(-6.28)	(0.14)	(3.03)	(-3.21)	(-2.03)	(-4.06)	(3.15)	(1.95)	(2.56)	
Foreign investor										
Lottery-like stocks	0.8834	-0.2411	-0.1552	-0.0031	0.6587	-0.1266	0.8418	0.0089	0.0311	59.76%
	(7.18)	(-2.15)	(-7.23)	(-3.14)	(-2.23)	(-3.19)	(8.94)	(0.21)	(2.45)	
Nonlottery-like stocks	0.3421	0.8843	-0.1478	0.0067	-0.6678	-0.3134	0.8417	0.0167	0.0318	59.98%
	(6.09)	(2.23)	(-3.37)	(3.23)	(-1.80)	(-2.11)	(8.93)	(0.33)	(2.81)	
Other stocks	0.7327	0.1211	0.2812	0.0003	-0.2734	-0.1145	0.8421	0.0286	0.0233	60.05%
	(5.78)	(1.04)	(4.46)	(1.21)	(-3.43)	(-3.38)	(8.91)	(0.52)	(2.12)	

Table 26 (Continued)
Investor Trading Activity and the Market Extremely Moves

Panel B: Market decrease	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	$Adj.R^2$
Retail investor										
Lottery-like stocks	0.8421 (3.21)	-0.2169 (-2.09)	0.3312 (3.98)	-0.0059 (-4.93)	0.5081 (0.81)	0.0911 (3.12)	0.1134 (7.32)	0.1532 (5.24)	-0.4068 (-5.32)	71.74%
Nonlottery-like stocks	0.0432 (3.13)	0.4112 (4.03)	-0.6123 (-3.97)	-0.0032 (-5.21)	0.4912 (2.31)	0.5834 (2.43)	0.8348 (8.34)	0.0311 (1.01)	0.0419 (4.12)	71.04%
Other stocks	0.2167 (3.26)	0.2187 (1.72)	-0.1679 (-5.12)	-0.0079 (-4.14)	0.2724 (1.61)	0.1473 (2.10)	0.0738 (8.32)	0.1534 (3.92)	-0.3231 (-4.03)	61.16%
Institutional investor										
Lottery-like stocks	-0.0321 (-5.13)	0.1843 (1.23)	0.0043 (0.22)	-0.0063 (-5.71)	-0.3339 (-1.56)	-0.2776 (-3.96)	0.8505 (3.11)	0.0893 (2.01)	0.0178 (1.21)	46.91%
Nonlottery-like stocks	-0.8326 (-4.27)	0.2156 (1.65)	-0.2684 (-1.82)	-0.0002 (-0.43)	-0.2381 (-1.37)	-0.2343 (-4.01)	0.8413 (2.02)	0.0878 (2.11)	0.0194 (1.65)	47.11%
Other stocks	-0.1911 (-6.15)	-0.0712 (-0.32)	0.2387 (2.12)	-0.0054 (-3.98)	-0.7462 (-2.01)	-0.3003 (-4.11)	0.8510 (1.32)	0.0716 (1.84)	0.0321 (2.16)	47.01%
Foreign investor										
Lottery-like stocks	0.8146 (6.91)	0.1052 (1.01)	-0.1618 (-8.12)	-0.0067 (-6.14)	-0.8643 (-3.02)	-0.0876 (-3.54)	0.8245 (8.42)	0.0173 (0.43)	0.0311 (2.32)	59.45%
Nonlottery-like stocks	0.8323 (6.23)	-0.1073 (-1.08)	-0.1778 (-7.45)	0.0084 (3.92)	-0.8874 (-3.15)	-0.0993 (-3.12)	0.8231 (8.39)	0.0154 (0.35)	0.0346 (2.12)	58.63%
Other stocks	0.7343 (6.01)	-0.0212 (-0.24)	-0.2834 (4.78)	0.0009 (1.16)	-0.1032 (-3.21)	-0.1457 (-3.23)	0.8323 (8.00)	0.0148 (0.56)	0.0234 (2.23)	60.42%

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Table 27
Buy-Sell Imbalance and the Market Extremely Moves

The table reports the estimated coefficients of the following time-series regression;

$$BSI_{j,t} = b_0 + b_1 DumMktMove*DumStockType_{j,t} + b_2 DumStockType_{j,t} + b_3 StockPrice_{j,t} + b_4 MktRet_{j,t} + b_5 MktRet_{j,t-1} + b_6 lnSETVol_{j,t} + b_7 lnSETVol_{j,t-1} + b_8 BSI_{j,t-1} + \varepsilon_{j,t}$$

$BSI_{j,t}$ is Buy-Sell imbalance in volume of investor *j* on day *t*. $DummyMktMove*DummyStockType_{j,t}$ is dummy variable for different stock types which set equal to one if it is the trading day after the Market increases (or decreases in Panel B) more than 3% and equal zero otherwise. $StockPrice_{j,t}$ is price of stock *i* on day *t*. $MktRet_{j,t}$ is the stock market return on day *t*. $MktRet_{j,t-1}$ is the stock market return on day *t-1*. $SETVol_{j,t}$ is the market trading volume on day *t*. $SETVol_{j,t-1}$ is the market trading volume on day *t-1*. $BSI_{j,t-1}$ is Buy-Sell imbalance in volume of investor *j* on day *t-1*. $\varepsilon_{j,t}$ is a mean-zero error term. The sample period is from January 1999 to December 2008. The White Heteroskedasticity Consistent Estimators for standards errors are employed. The *t-statistics* are presented in the parentheses below the estimated coefficients.

Panel A: Mkt increase	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	$Adj.R^2$
Retail investor										
Lottery-like stocks	-0.1347	-0.0692	0.0235	-0.0002	0.0442	0.3621	0.0243	-0.0159	0.0925	23.11%
	(-5.32)	(-3.04)	(2.32)	(-3.18)	(3.41)	(3.98)	(4.98)	(-3.16)	(7.86)	
Nonlottery-like stocks	-0.1288	-0.0732	-0.0137	-0.0001	0.0312	0.0415	0.3056	-0.0187	0.0966	23.13%
	(-5.06)	(-3.91)	(-3.02)	(-2.98)	(3.32)	(3.85)	(3.91)	(-3.07)	(7.51)	
Other stocks	-0.1314	0.0309	0.0064	-0.0004	0.9745	-0.2385	0.0315	-0.0179	0.0961	23.17%
	(-5.36)	(1.89)	(1.96)	(-3.01)	(3.01)	(-3.34)	(4.81)	(-3.15)	(7.76)	
Institutional investor										
Lottery-like stocks	-0.2134	-0.1045	-0.0901	-0.0001	0.2922	-0.0297	0.0411	-0.0356	0.2807	10.91%
	(-2.13)	(-1.34)	(-6.21)	(-2.97)	(2.31)	(-5.13)	(2.23)	(-1.47)	(3.34)	
Nonlottery-like stocks	-0.2501	0.0145	0.0699	0.0007	0.9245	-0.0171	0.0131	-0.0155	0.2808	10.43%
	(-2.94)	(2.02)	(5.01)	(1.31)	(2.58)	(-5.06)	(2.15)	(-1.52)	(3.12)	
Other stocks	-0.0112	0.0508	0.0134	-0.0003	0.8123	-0.0199	0.0129	-0.0148	0.2799	10.01%
	(-2.20)	(1.74)	(0.96)	(-1.98)	(2.59)	(-5.11)	(2.01)	(-1.57)	(3.17)	
Foreign investor										
Lottery-like stocks	-0.5028	-0.0876	-0.0834	-0.0008	0.0617	0.5911	0.0354	0.0071	0.2519	22.64%
	(-7.25)	(-1.23)	(-3.37)	(-2.11)	(3.13)	(5.90)	(3.10)	(0.13)	(7.01)	
Nonlottery-like stocks	-0.5067	0.1905	0.0202	0.0011	0.0798	0.5916	0.0328	-0.0072	0.2319	22.87%
	(-7.13)	(4.54)	(2.01)	(0.36)	(3.09)	(5.89)	(3.12)	(-0.14)	(7.18)	
Other stocks	-0.3465	0.0434	0.0218	0.0007	0.9101	0.5912	0.0331	0.0073	0.2325	22.61%
	(-7.43)	(0.72)	(2.20)	(1.63)	(3.29)	(5.93)	(3.01)	(0.12)	(7.19)	

Table 27 (Continued)
Buy-Sell Imbalance and the Market Extremely Moves

Panel A: Market decrease	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	$Adj.R^2$
Retail investor										
Lottery-like stocks	-0.1143	0.0199	0.0065	-0.0004	0.9611	-0.3027	0.0274	-0.0181	0.0989	25.34%
	(-3.45)	(0.96)	(1.87)	(-3.94)	(4.60)	(-4.26)	(4.56)	(-3.11)	(7.81)	
Nonlottery-like stocks	-0.1121	0.0122	-0.0145	-0.0007	0.9614	-0.3021	0.0271	-0.0179	0.0990	25.89%
	(-3.14)	(1.64)	(-3.23)	(-3.01)	(4.61)	(-4.19)	(4.55)	(-3.00)	(7.80)	
Other stocks	-0.115	0.0115	0.0061	-0.0008	0.9609	-0.3085	0.0271	-0.0178	0.0972	25.76%
	(-3.29)	(0.76)	(1.52)	(-5.41)	(4.68)	(-4.27)	(4.59)	(-3.02)	(7.82)	
Institutional investor										
Lottery-like stocks	-0.2316	-0.0923	-0.0897	-0.0003	0.6787	-0.5655	0.0491	-0.0311	0.2692	11.76%
	(-2.73)	(-1.31)	(-6.12)	(-0.23)	(2.98)	(-4.11)	(2.49)	(-1.78)	(3.46)	
Nonlottery-like stocks	-0.2514	0.0727	0.0541	0.0011	0.6812	-0.5658	0.0494	-0.0245	0.2715	11.65%
	(-2.91)	(1.11)	(5.01)	(1.63)	(3.01)	(-3.99)	(2.43)	(-1.51)	(3.32)	
Other stocks	-0.2432	-0.0123	0.0113	-0.0002	0.6895	-0.5691	0.0498	-0.0301	0.2774	11.32%
	(-2.43)	(-0.12)	(0.87)	(-5.42)	(3.07)	(-4.07)	(2.41)	(-1.62)	(4.12)	
Foreign investor										
Lottery-like stocks	-0.5134	0.1136	-0.0243	-0.0003	0.6326	0.6578	0.0384	0.0051	0.2361	23.65%
	(-8.64)	(1.12)	(-4.01)	(-3.11)	(2.65)	(5.67)	(2.43)	(0.43)	(7.08)	
Nonlottery-like stocks	-0.5122	0.0344	0.091	0.0004	0.6389	0.6589	0.0383	0.0023	0.2386	23.34%
	(-8.37)	(1.16)	(1.17)	(1.10)	(2.68)	(5.69)	(2.46)	(0.21)	(7.07)	
Other stocks	-0.5167	0.0245	0.0165	-0.0001	0.6315	0.6571	0.0386	0.0027	0.2388	23.27%
	(-8.79)	(0.88)	(2.12)	(-1.98)	(2.69)	(5.65)	(2.49)	(0.19)	(7.09)	

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Table 28
Gambling Seasonality and the Market Extremely Moves

This table reports the estimated coefficients of the GJR-GARCH model. In this model, the autoregressive processes are used to correct the autocorrelation in stock returns. The sample period is from January 1999 to December 2008. Specifically, the following GARCH models are estimated;

$$R_{i,t} = \alpha_0 + \sum_{j=1}^{k} \phi_j R_{i,t-j} + \alpha_1 DummySeasonalVariable_{i,t} + \varepsilon_{i,t},$$

$$\varepsilon_{i,t} \big| \Omega_{i,t-1} \approx N(0, h_{i,t}),$$

$$h_{i,t} = \omega + \delta \varepsilon^2_{i,t-1} + \gamma \varepsilon^2_{i,t-1} D_{i,t-1} + \theta h_{i,t-1}$$

$R_{i,t}$ denotes the stock *i* daily return on day *t*. $R_{i,t-j}$ denotes the stock *i* daily return on day *t-j*. $DummySeasonalVariable_{i,t}$ is a dummy variable set equal to one if it is the trading day that Market increases (decreases) more than 3% in Panel A (Panel B) and equal zero otherwise. Ω_{t-1} is the information set at time *t-1*. D_{t-1} is a dummy variable that allow good news and bad news to have different impacts on the conditional variance. Where D_{t-1} equal to one if ε_{t-1} is less than zero (bad news), and D_{t-1} equals zero (good news) otherwise. The good news has only δ impact on volatility, while the bad news has a $\delta + \gamma$. The AIC and SIC are utilized for determining the optimal lags of returns. The *t-statistics* are reported in the parentheses below the estimated coefficients.

Panel A: Trading day that the Market increases more than 3%

	α_0	ϕ_1	ϕ_2	ϕ_3	α_1	ω	δ	γ	θ
Lottery-like stocks	-0.00026 (-0.61)	0.0824 (3.45)	0.1064 (4.03)	0.0682 (2.51)	0.0331 (5.45)	0.00002 (4.34)	0.2017 (7.84)	-0.1075 (-4.29)	0.8262 (13.10)
Nonlottery-like stocks	-0.00009 (-0.41)	0.0915 (3.94)	0.0749 (2.88)	0.0252 (0.92)	0.0217 (6.41)	0.000006 (5.30)	0.1174 (6.17)	-0.0458 (-2.24)	0.8589 (16.17)
Other stocks	-0.00005 (-0.17)	0.8899 (3.61)	0.1143 (4.03)	0.0419 (1.40)	0.0302 (6.17)	0.00001 (5.61)	0.2359 (7.48)	-0.1363 (-4.46)	0.7896 (13.90)

Panel B: Trading day that the Market decreases more than 3%

	α_0	ϕ_1	ϕ_2	ϕ_3	α_1	ω	δ	γ	θ
Lottery-like stocks	0.0012 (2.89)	0.0631 (2.78)	0.0813 (3.25)	0.0201 (0.77)	-0.0502 (-5.64)	0.00001 (3.44)	0.1644 (7.46)	-0.0787 (-3.89)	0.8650 (13.54)
Nonlottery-like stocks	0.0009 (4.78)	0.0471 (2.22)	0.0373 (1.57)	-0.0285 (-1.11)	-0.0342 (-3.85)	0.000001 (3.74)	0.0731 (5.04)	-0.0204 (-2.58)	0.9225 (16.58)
Other stocks	0.0012 (4.40)	0.0708 (3.10)	0.0649 (2.31)	0.0003 (0.01)	-0.0439 (-3.74)	0.000004 (3.66)	0.1817 (6.02)	-0.0984 (-3.71)	0.8569 (15.51)

Table 29
Gambling Seasonality on the Trading Day After the Market Extremely Moves

This table reports the estimated coefficients of the GJR-GARCH model. In this model, the autoregressive processes are used to correct the autocorrelation in stock returns. The sample period is from January 1999 to December 2008. Specifically, the following GARCH models are estimated;

$$R_{i,t} = \alpha_0 + \sum_{j=1}^{k} \phi_j R_{i,t-j} + \alpha_1 DummySeaso\ nalVariabl\ e_{i,t} + \varepsilon_{i,t},$$

$$\varepsilon_{i,t} \big| \Omega_{i,t-1} \approx N(0, h_{i,t}),$$

$$h_{i,t} = \omega + \delta\varepsilon_{i,t-1}^2 + \gamma\varepsilon_{i,t-1}^2 D_{i,t-1} + \theta h_{i,t-1}$$

$R_{i,t}$ denotes the stock *i* daily return on day *t*. $R_{i,t-j}$ denotes the stock *i* daily return on day *t-j*. $DummySeasonalVariable_{i,t}$ is a dummy variable set equal to one if it is the trading day after the Market increases (decreases) more than 3% in Panel A (Panel B) and equal zero otherwise. Ω_{t-1} is the information set at time *t-1*. D_{t-1} is a dummy variable that allow good news and bad news to have different impacts on the conditional variance. Where D_{t-1} equal to one if ε_{t-1} is less than zero (bad news), and D_{t-1} equals zero (good news) otherwise. The good news has only δ impact on volatility, while the bad news has a $\delta + \gamma$. The AIC and SIC are utilized for determining the optimal lags of returns. The *t-statistics* are reported in the parentheses below the estimated coefficients.

	α_0	$ø_1$	$ø_2$	$ø_3$	α_1	ω	δ	γ	θ
Panel A: Trading day after the Market increases more than 3%									
Lottery-like stocks	0.0004 (1.05)	0.0987 (3.95)	0.0962 (3.56)	0.0498 (1.78)	-0.0051 (-1.55)	0.00002 (4.30)	0.2354 (8.50)	-0.135 (-5.09)	0.8158 (14.44)
Nonlottery-like stocks	0.0003 (1.42)	0.0973 (3.87)	0.0765 (2.82)	-0.0019 (-0.06)	-0.0013 (-0.73)	0.00007 (5.85)	0.1404 (6.55)	-0.0583 (-2.65)	0.8445 (14.00)
Other stocks	0.0006 (2.21)	0.1122 (4.17)	0.0927 (3.15)	0.0141 (0.45)	-0.0045 (-1.94)	0.00001 (5.29)	0.2977 (8.55)	-0.1826 (-5.61)	0.7752 (13.10)
Panel B: Trading day after the Market decreases more than 3%									
	α_0	$ø_1$	$ø_2$	$ø_3$	α_1	ω	δ	γ	θ
Lottery-like stocks	0.0004 (0.85)	0.0922 (3.67)	0.0974 (3.61)	0.0517 (1.85)	0.0013 (0.30)	0.00002 (4.31)	0.2335 (8.42)	-0.1322 (-4.98)	0.8154 (14.17)
Nonlottery-like stocks	0.0003 (1.15)	0.1029 (4.02)	0.0778 (2.88)	-0.0001 (-0.01)	0.0028 (1.28)	0.00007 (4.26)	0.1384 (5.03)	-0.0563 (-2.42)	0.8456 (13.80)
Other stocks	0.0005 (1.91)	0.1043 (3.92)	0.0953 (3.23)	0.0189 (0.61)	0.0034 (1.09)	0.00001 (5.36)	0.2955 (8.41)	-0.1773 (-5.43)	0.7724 (13.04)

Table 30
BSI and Lottery-like Stock Returns
Vector Autoregression and Granger Causality Tests

This table reports the vector auto-regression estimates and the Granger causality tests for the following vector auto-regression model of order one (VAR (1));

$$BSI_{j,t} = \beta_0 + \beta_1 LotR_{j,t-1} + \beta_2 BSI_{j,t-1} + \delta_{j,t}$$

$$LotR_{j,t} = \alpha_0 + \alpha_1 LotR_{j,t-1} + \alpha_2 BSI_{j,t-1} + \varepsilon_{j,t}$$

$BSI_{j,t}$ denotes the Buy-Sell imbalance of investor *j* on day *t*. $BSI_{j,t-1}$ is the Buy-Sell imbalance of investor *j* on day *t-1*. $LotRet_{j,t}$ is the mean daily return of lottery-like stocks on day *t*. $LotRet_{j,t-1}$ is the mean daily return of lottery-like stocks return on day *t-1*. Panel A reports the vector auto-regression estimates for the sample period from January 1999 to December 2008. The *t-statistics* are reported in the parentheses below the estimated coefficients. In Panel B, the Chi-Square and probability from the Granger causality estimates are shown.

Panel A: Vector Auto-Regression Estimation

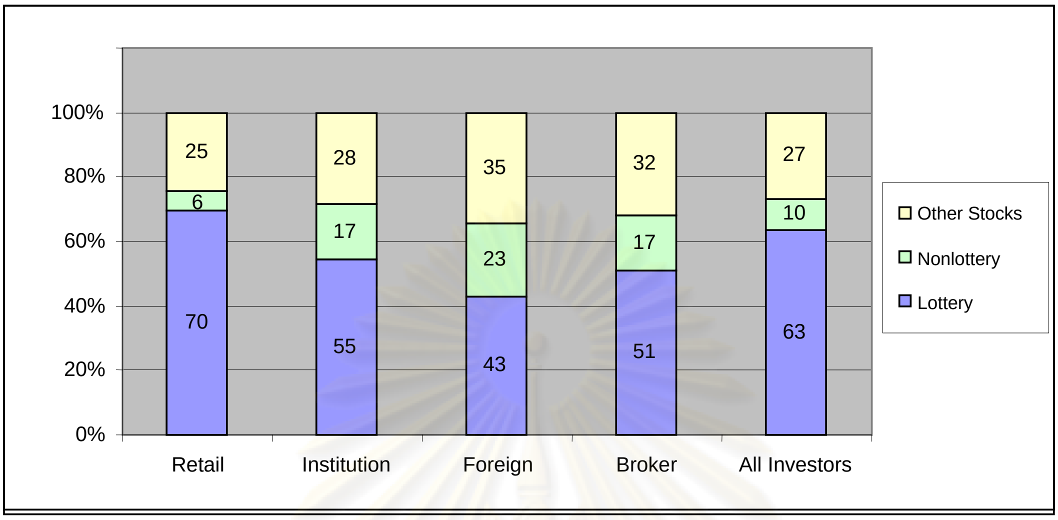
	Constant	***$LotReturn_{t-1}$***	***BSI_{t-1}***	***Adj. R^2***
Retail investor				
BSI_t	-0.0563 (-0.61)	0.9382 (3.42)	0.1542 (7.22)	28.67%
$LotReturn_t$	0.0015 (2.46)	0.1472 (6.87)	0.0002 (1.95)	23.91%
Institutional investor				
BSI_t	-0.5307 (-5.89)	0.6956 (2.83)	0.3459 (17.11)	19.35%
$LotReturn_t$	0.0017 (2.73)	0.1497 (7.02)	0.0003 (1.89)	12.47%
Foreign investor				
BSI_t	0.1052 (0.99)	-0.4668 (-1.48)	0.2213 (10.52)	16.72%
$LotReturn_t$	0.0015 (2.48)	0.1504 (7.06)	-0.0002 (-1.84)	12.98%

Panel B: Granger Causality Wald Test

	Chi-Square	**Probability**
Retail investor		
Granger-non Causality from		
BSI to LotReturn	2.70	0.1003***
LotReturn to BSI	2.42	0.1202***
Institutional investor		
Granger-non Causality from		
BSI to LotReturn	2.58	0.1084***
LotReturn to BSI	3.56	0.0590*
Foreign investor		
Granger-non Causality from		
BSI to LotReturn	2.18	0.1396***
LotReturn to BSI	3.37	0.0664*

APPENDIX B

A: Percentage of Daily Trading Volume (shares)



B: Percentage Daily Trading Value (baht)

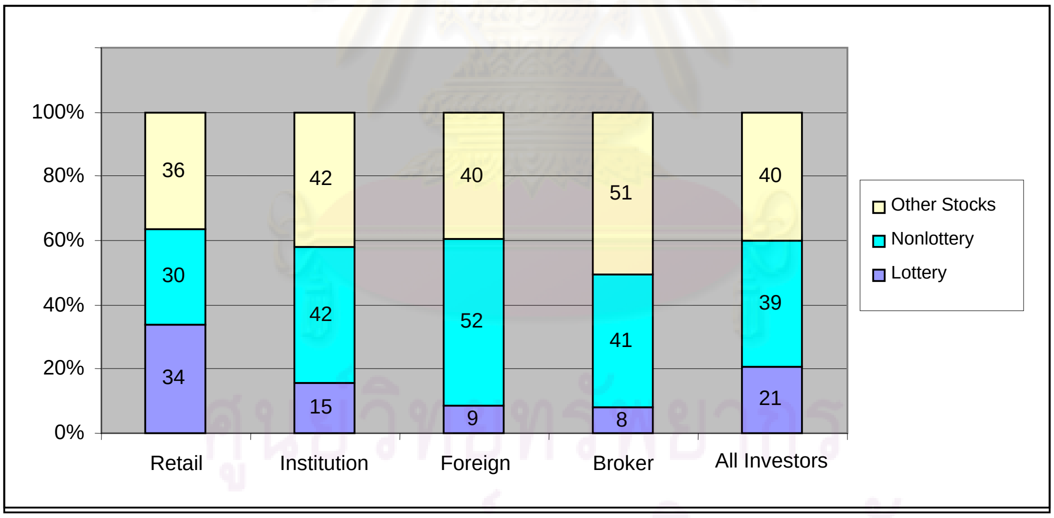


Figure 1
Percentage of the Daily Trading Volume and Value

This figures display the percentage of the average daily trading volume and value during the sample period from 1999 to 2008. Figure 1A shows the average daily trading volume in share across different investor types. Figure 1B shows the average daily trading value in baht across different investor types. Investors are classified into four types; retail investors, institutional investors, foreign investors, and broker-owned portfolio. The proportion trades of all investors are also shown in both figures.

Daily Percentage of Lottery-like Stock Trading

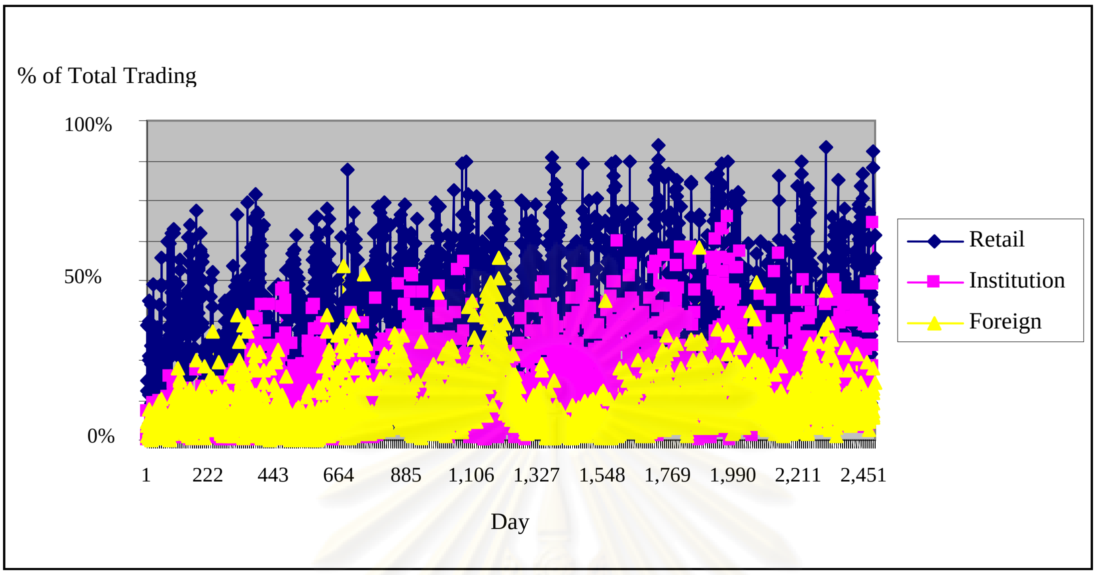
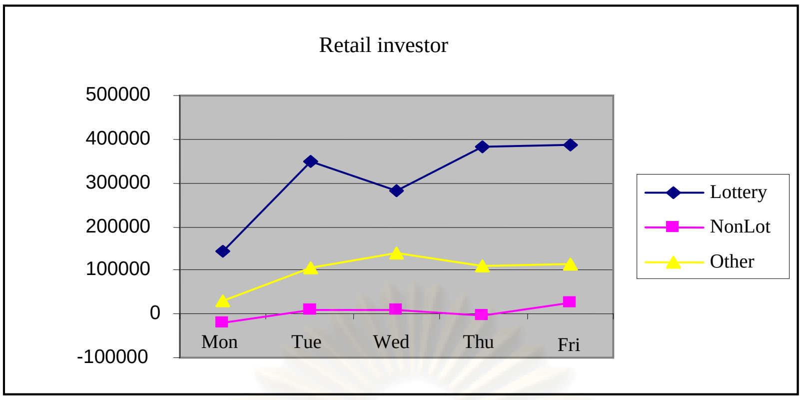


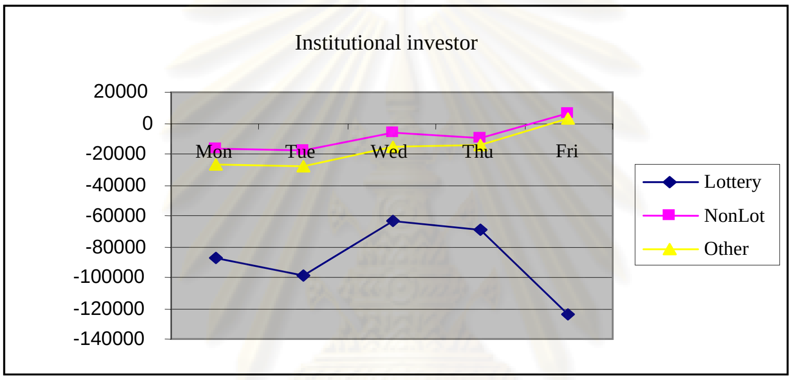
Figure 2
Daily Percentage of Lottery-like Stock Trading Value

This figure illustrates the time-series plot of the percentage of lottery-like stocks daily trading value during the sample period from 1999 to 2008. Percentage of lottery-like stocks trading is computed as the proportion of lottery-like stock trading to the total stock trading by each investor types for each trading day. There are 2,451 trading days during our sample period. The plot shows daily percentage of lottery-like stocks trading across different investor types.

A: Daily Net Buy of Retail Investor



B: Daily Net Buy of Institutional Investor



C: Daily Net Buy of Foreign Investor

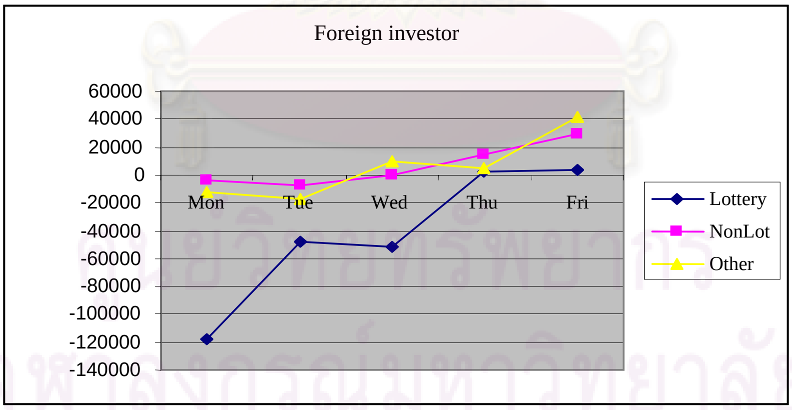
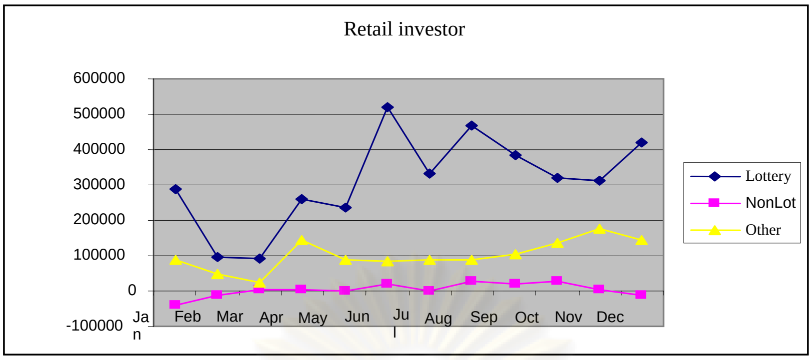


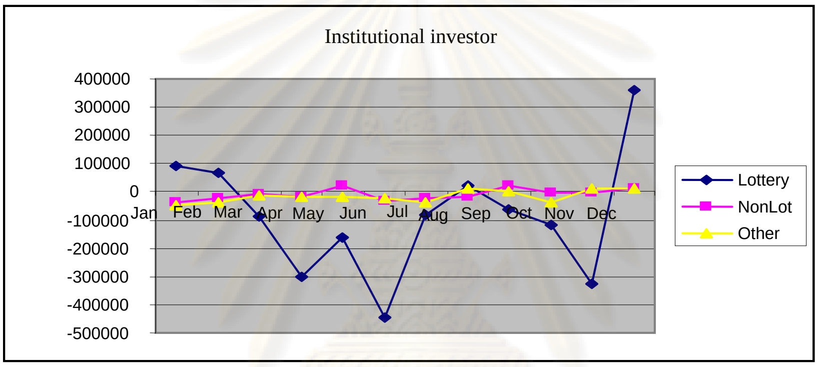
Figure 3
Daily Net Buy Volume of Different Investor Types: Day-of-the Week Analysis

The figures display the daily net buy of different investor types during the sample period from 1999 to 2008. The mean daily net buy volume for three stock types; lottery-like stocks, nonlottery-like stocks and the other stocks, are calculated for each day-of-the-week. Figure 3A shows the daily net buy of retail investors. Figure 3B shows the daily net buy of institutional investors. Figure 3C shows the daily net buy of foreign investors.

A: Daily Net Buy of Retail Investor



B: Daily Net Buy of Institutional Investor



C: Daily Net Buy of Foreign Investor

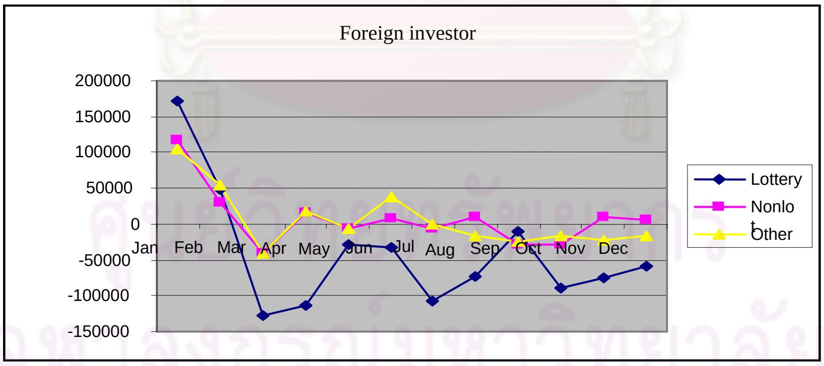


Figure 4
Daily Net Buy Volume of Different Investor Types: Month-by-Month Analysis

The figures display the daily net buy across different investor types during the sample period from 1999 to 2008. The mean daily net buy volume for three stock types; lottery-like stocks, nonlottery-like stocks and the other stocks, are calculated month by month. Figure 4A shows the daily net buy of retail investors. Figure 4B shows the daily net buy of institutional investors. Figure 4C shows the daily net buy of foreign investors.

APPENDIX C

This appendix presents a supplementary examination on gambling demand of investors after experiencing outcome payoff in prior round of gambling; the analysis of gambling seasonality and the football effect.

Several psychology literatures suggest that sporting event can affect human behavior. For example, Edman et al. (2007) investigate the effect of sports sentiment on stock prices. They use sport outcomes to capture mood changes among investors and find that losses in soccer matches have an economically and statistically significant negative effect on the losing in stock market. Currently, the English Premier League is the most popular football league worldwide and in Thailand. The effect of sport results leads to sudden mood changes which can impact a trading decision in the stock market. If there is relatively high emotional action to the stock market on trading day after the football game, the preference on lottery-like stock would be greater relative to non-lottery-like stocks on the trading day after the football games.

We use the outcomes of Manchester United and Liverpool team in our investigation because these two teams are the most famous football teams among Thai fans. The English Premier League football outcomes are drawn from the Soccerbase website. During our sample period, Manchester Untied play 378 matches; they win 256 matches (67.72%), lose 52 matches (13.76%), and equal 70 matches (18.52%).There are 380 matches of Liverpool; they win 210 matches (55.26%), lose 73 matches (19.21%), and equal 97 matches (25.53%). There are 17 matches that Manchester United competed with Liverpool; Manchester United win 8 matches, lose 6 matches, and equal 3 matches. We investigate the football effect in various aspects, include (i) Liverpool wins, (ii) Liverpool loses, (iii) Manchester United wins, (iv) Manchester United loses, and the joint effect which are (v) Liverpool wins and Manchester United Wins, (vi) Liverpool wins and Manchester United loses, (vii) Liverpool loses and Manchester United Wins, and (viii) Liverpool loses and Manchester United loses.

Table C1 presents the trading volume regression results on the trading day after Manchester United or Liverpool wins (loses) in Panel A (B). Overall, the estimated coefficients of lottery-like stock are insignificant for three investor types. There is no difference in trading volume of lottery-like stock for any investor types on trading day after the football games. Table C2 presents the BSI of each investor types on the trading day after the football teams win (lose) in Panel A (B). There is also no difference in Buy-Sell imbalance level across investor types on trading day after the famous football games. We also examine the volume trading, BSI, and the football effects on (i) trading day after Manchester United wins, (ii) trading day after Manchester United loses, (iii) trading day after Liverpool wins, (iv) trading day after Liverpool loses, (v) trading day after the Manchester United wins and Liverpool wins, (vi) trading day after Manchester United wins and Liverpool loses, (vii) trading day after Manchester United loses and Liverpool wins, and (viii) trading day after Manchester United loses and Liverpool loses. Overall, we find no association between investor trading activity and the football outcome effects.

The results of football outcomes on stock return are presented in Table C3. We expect to observe the α_2 of lottery-like stock to be significant and positive on the trading day after the famous football matches. In the analysis of football effects, we control for Monday effect since most of the football games play during the weekend then the first trading day after the game is Monday. The estimated coefficients (α_2) of lottery-like stock returns and other stocks are insignificant in all cases. Only the α_2 of nonlottery-like stock is significant and positive on the trading day after Liverpool team loss (Panel D). Table C4 reports in the joint effect of the football outcomes. Panel A presents the regression results on the trading day after the Manchester United win and Liverpool loss. Only the α_2 of nonlottery-like stock is significant and positive. Panel B presents the results of the regression on the trading day after Manchester United loss and Liverpool Wins. The α_2 of lottery-like stock is significant and positive only on this joint effect. The estimated coefficients (α_2) in Panel C and D are all insignificant. Overall, results indicate there is significant higher return of lottery-like stock on the trading day after Manchester United loss and Liverpool win. We find little relation between football outcomes, lottery-like stock return but this relation cannot link to gambling demand of retail investors.

Table C1
Trading Activity after the Famous Football Games

The table reports the estimated coefficients of the following time-series regression;

$$ln(Total\ trading\ volume)_{j,t} = b_0 + b_1\ DummyFootBall*DummyStockType_{j,t} + b_2\ DummyStockType_{j,t} + b_3 MktRet_{jt} + b_4\ MktRet_{j,t-1} + b_5\ lnSETVol_{j,t} + b_6\ lnSETVol_{j,t-1} + b_7 ln(Total\ trading\ volume)_{j,t-1} + \varepsilon_{j,t}$$

Total trading volume$_{j,t}$ is volume buy-initiated plus volume sell-initiated by investor *j* on day *t*. *DummyFootBall*DummyStockType*$_{j,t}$ is dummy variable for different stock types which set equal to one if it is the trading day after the famous football teams win (lose in Panel B) and equal zero otherwise. *MktRet*$_{j,t}$ is the stock market return on day *t*. *MktRet*$_{j,t-1}$ is the stock market return on day *t-1*. *SETVol*$_{j,t}$ is the market trading volume on day *t*. *SETVol*$_{j,t-1}$ is the market trading volume on day *t-1*. *Total trading volume*$_{j,t-1}$ is Total volume purchased and sold by investor *j* on day *t-1*. $\varepsilon_{j,t}$ is a mean-zero error term. The sample period is from January 1999 to December 2008. The White Heteroskedasticity Consistent Estimators for standards errors are employed. The *t-statistics* are presented in the parentheses below the estimated coefficients.

Panel A: Football win	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	**Adj.R^2**
Retail investor									
Lottery-like stocks	0.7841 (3.84)	-0.0777 (-1.44)	0.3273 (6.89)	0.8924 (1.48)	0.1947 (3.73)	0.1092 (3.73)	0.1653 (5.66)	-0.4070 (-5.62)	68.06%
Nonlottery-like stocks	0.0432 (3.44)	0.0058 (0.13)	0.5972 (-8.00)	0.7788 (1.34)	0.4629 (2.58)	0.8437 (9.33)	0.0178 (0.63)	-0.0445 (-4.48))	70.30%
Other stocks	0.2072 (3.50)	-0.0528 (-0.89)	-0.1651 (-4.71)	0.8812 (1.17)	0.1118 (2.87)	0.0775 (8.66)	0.1497 (4.08)	-0.3613 (-4.20)	50.08%
Institutional investor									
Lottery-like stocks	-0.0316 (-5.88)	0.0119 (0.17)	0.0109 (0.38)	-0.6619 (-2.07)	-0.3204 (-4.25)	0.8565 (3.47)	0.0796 (2.03)	0.0159 (1.33)	45.67%
Nonlottery-like stocks	-0.8535 (-4.89)	-0.0998 (-1.63)	-0.2674 (-9.69)	-0.6388 (-2.05)	-0.2417 (-4.18)	0.8452 (1.35)	0.0814 (2.11)	0.0198 (1.68)	46.77%
Other stocks	-0.1796 (-6.75)	-0.0297 (-0.49)	0.2782 (4.01)	-0.6741 (-2.10)	-0.2639 (-4.21)	0.8492 (3.44)	0.0765 (1.98)	0.0319 (2.68)	46.75%
Foreign investor									
Lottery-like stocks	0.8841 (7.20)	-0.0494 (-1.09)	-0.1535 (-7.49)	-0.0553 (-3.57)	-0.0860 (-3.71)	0.8256 (8.60)	0.0149 (0.54)	0.0307 (2.62)	58.25%
Nonlottery-like stocks	0.7817 (6.97)	-0.0038 (-0.91)	0.4763 (3.01)	-0.0616 (-3.57)	-0.1126 (-3.82)	0.8516 (4.96)	0.0127 (0.57)	0.0230 (2.12)	58.89%
Other stocks	0.7399 (6.04)	-0.0056 (-0.01)	0.2874 (4.33)	-0.0534 (-3.61)	-0.1179 (-3.81)	0.8294 (4.07)	0.0139 (0.51)	0.0278 (2.42)	59.17%

Table C1 (Continued)
Trading Activity after the Famous Football Games

Panel B: Football lose	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	Adj.R^2
Retail investor									
Lottery-like stocks	0.7838 (3.81)	-0.0661 (-0.86)	0.3196 (3.69)	0.9009 (1.49)	0.1702 (3.69)	0.1047 (7.17)	0.1641 (5.62)	-0.4071 (-5.61)	68.05%
Nonlottery-like stocks	0.0431 (6.45)	0.0292 (0.36)	-0.5978 (-7.01)	0.7787 (1.34)	0.4503 (2.57)	0.8445 (9.34)	0.1748 (0.62)	0.0431 (4.49)	70.33%
Other stocks	0.2097 (3.49)	0.0012 (0.01)	-0.1724 (-5.01)	0.8842 (1.17)	0.0839 (2.83)	0.0796 (8.71)	0.1477 (4.03)	-0.3618 (-4.20)	50.07%
Institutional investor									
Lottery-like stocks	-0.0316 (-5.88)	-0.0787 (-0.73)	0.0162 (0.58)	-0.6578 (-2.06)	-0.3057 (-4.23)	0.8546 (2.41)	0.0812 (2.08)	0.0160 (1.34)	45.88%
Nonlottery-like stocks	-0.8590 (-4.92)	-0.0769 (-0.78)	-0.0278 (-10.41)	-0.6197 (-2.03)	-0.2829 (-4.23)	0.8475 (1.40)	0.0796 (2.06)	0.0198 (1.68)	46.75%
Other stocks	-0.1872 (-6.76)	-0.0594 (-0.60)	0.2768 (10.30)	-0.6699 (-2.09)	-0.2686 (-4.21)	0.8492 (3.43)	0.0768 (1.99)	0.0319 (2.68)	46.69%
Foreign investor									
Lottery-like stocks	0.8823 (7.19)	-0.1247 (-1.30)	-0.1542 (-7.80)	0.0435 (-3.55)	0.0806 (3.70)	0.8244 (8.56)	0.0162 (0.58)	0.0308 (2.63)	58.26%
Nonlottery-like stocks	0.8182 (7.55)	-0.1324 (-0.69)	0.3871 (2.18)	-0.0533 (-3.67)	-0.1145 (-3.75)	0.8336 (8.69)	0.0119 (0.49)	0.0437 (2.48)	58.56%
Other stocks	0.7362 (6.04)	0.0104 (0.14)	0.2868 (4.81)	-0.0596 (-3.61)	-0.1298 (-3.81)	0.8293 (8.08)	0.0137 (0.50)	0.0276 (2.42)	59.13%

Table C2
Buy-Sell Imbalance and the Famous Football Games

The table reports the estimated coefficients of the following time-series regression;

$$BSI_{j,t} = b_0 + b_1\, DummyFootBall{*}DummyStockType_{j,t} + b_2 DummyStockType_{j,t} + b_3 MktRet_{j,t} + b_4 MktRet_{j,t-1} + b_5 lnSETVol_{j,t} + b_6\, lnSETVol_{j,t-1} + b_7 BSI_{j,t-1} + \varepsilon_{j,t}$$

$BSI_{j,t}$ is Buy-Sell imbalance in volume of investor *j* on day *t*. $DummyFootBall{*}DummyStockType_{j,t}$ is dummy variable for different stock types which set equal to one if it is the trading day after the famous football teams win (lose in Panel B) more than 3% and equal zero otherwise. $MktRet_{j,t}$ is the stock market return on day *t*. $MktRet_{j,t-1}$ is the stock market return on day *t-1*. $SETVol_{j,t}$ is the market trading volume on day *t*. $SETVol_{j,t-1}$ is the market trading volume on day *t-1*. $BSI_{j,t-1}$ is Buy-Sell imbalance in volume of investor *j* on day *t-1*. $\varepsilon_{j,t}$ is a mean-zero error term. The sample period is from January 1999 to December 2008. The White Heteroskedasticity Consistent Estimators for standards errors are employed. The *t-statistics* are presented in the parentheses below the estimated coefficients.

Panel A: Football win	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	$Adj.R^2$
Retail investor									
Lottery-like stocks	-0.1315	-0.0096	0.0094	0.9172	-0.3062	0.0276	-0.0176	0.0918	22.98%
	(-5.49)	(-1.05)	(2.30)	(5.10)	(-3.25)	(4.84)	(-3.11)	(7.85)	
Nonlottery-like stocks	-0.1291	-0.0165	-0.0124	0.9177	-0.2998	0.0289	-0.0171	0.0907	22.79%
	(-5.18)	(-1.58)	(-3.04)	(6.13)	(-3.20)	(4.80)	(-3.08)	(7.76)	
Other stocks	-0.1364	-0.0078	0.0077	0.9163	-0.3075	0.0275	-0.0176	0.0961	22.64%
	(-5.47)	(-0.86)	(1.90)	(5.10)	(-3.27)	(4.84)	(-3.12)	(7.87)	
Institutional investor									
Lottery-like stocks	0.2305	0.0539	-0.0975	0.4826	-0.5972	0.0475	0.0473	0.2698	10.51%
	(-2.71)	(1.45)	(-6.78)	(6.25)	(-4.08)	(2.46)	(2.46)	(5.48)	
Nonlottery-like stocks	0.2568	0.0096	0.0702	0.8902	-0.5886	0.0447	0.0316	0.2719	10.30%
	(-2.94)	(0.31)	(5.07)	(12.26)	(-4.05)	(2.30)	(1.64)	(5.71)	
Other stocks	0.2189	0.0069	0.0109	0.8953	-0.6173	0.0439	0.0312	0.2771	10.02%
	(-2.50)	(0.23)	(0.79)	(5.24)	(-4.10)	(2.24)	(1.65)	(5.21)	
Foreign investor									
Lottery-like stocks	-0.5577	-0.0279	-0.0279	0.4372	0.5271	0.0347	0.0283	0.2367	21.87%
	(-10.48)	(-1.44)	(-3.17)	(2.11)	(5.97)	(2.91)	(0.24)	(5.07)	
Nonlottery-like stocks	-0.5715	-0.0027	0.0119	0.4297	0.4939	0.0357	0.0018	0.2334	21.71%
	(-10.72)	(-0.14)	(1.38)	(2.08)	(5.85)	(2.99)	(0.15)	(5.26)	
Other stocks	-0.5742	-0.0135	0.0217	0.4216	0.5043	0.0353	0.0022	0.2382	21.76%
	(-10.77)	(-0.70)	(2.50)	(2.09)	(5.89)	(2.95)	(0.19)	(5.21)	

Table C2 (Continued)
Buy-Sell Imbalance and the Famous Football Games

Panel B: Football lose	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	Adj.R^2
Retail investor									
Lottery-like stocks	-0.1372 (-5.51)	-0.0101 (-0.68)	0.0085 (2.16)	0.9145 (6.11)	-0.3079 (-3.28)	0.0277 (4.86)	-0.0177 (-3.13)	0.0918 (7.85)	22.73%
Nonlottery-like stocks	-0.1297 (-5.21)	-0.0255 (-1.52)	-0.0135 (-3.42)	0.9156 (6.15)	-0.2983 (-3.21)	0.0273 (4.81)	-0.0174 (-3.08)	0.0905 (7.74)	22.79%
Other stocks	-0.1367 (-5.49)	-0.0115 (-0.77)	0.0072 (1.83)	0.9189 (6.10)	-0.3042 (-3.29)	0.0298 (4.85)	-0.0177 (-3.12)	0.0922 (7.88)	22.64%
Institutional investor									
Lottery-like stocks	-0.2328 (-2.68)	-0.0525 (-0.98)	-0.0876 (-6.31)	0.8764 (4.24)	-0.5626 (-4.00)	0.0448 (2.31)	-0.0297 (-1.54)	0.2693 (3.47)	10.58%
Nonlottery-like stocks	-0.2563 (-2.94)	-0.0038 (-0.08)	0.0717 (5.36)	0.8896 (2.25)	-0.5823 (-4.04)	0.0442 (2.27)	-0.0312 (-1.62)	0.2721 (4.72)	10.30%
Other stocks	-0.2186 (-2.50)	0.0074 (0.15)	0.0116 (0.87)	0.8943 (2.24)	-0.6082 (-4.10)	0.0458 (2.24)	-0.0318 (-1.65)	0.2776 (4.22)	9.97%
Foreign investor									
Lottery-like stocks	-0.5584 (-2.49)	-0.0476 (-1.52)	-0.0291 (-3.48)	0.4302 (3.13)	0.5197 (5.95)	0.0349 (2.90)	0.0029 (0.25)	0.2371 (3.10)	21.87%
Nonlottery-like stocks	-0.5715 (-2.72)	-0.02957 (-0.94)	0.0129 (1.55)	0.4318 (3.09)	0.5018 (5.87)	0.0351 (2.96)	0.0024 (0.20)	0.2387 (3.27)	21.72%
Other stocks	-0.5749 (-2.78)	-0.0117 (-0.37)	0.0203 (2.43)	0.4312 (3.11)	0.5022 (5.87)	0.0356 (2.97)	0.0020 (0.17)	0.2380 (3.20)	21.75%

Table C3
Gambling Seasonality and the Football Effects

This table reports the estimated coefficients of the GJR-GARCH model. In this model, the autoregressive processes are used to correct the autocorrelation in stock returns. The sample period is from January 1999 to December 2008. Specifically, the following GARCH models are estimated;

$$R_{i,t} = \alpha_0 + \sum_{j=1}^{k} \phi_j R_{i,t-j} + \alpha_1 DummyMonday_{i,t} + \alpha_2 DummyFootballOutcome_{i,t} + \varepsilon_{i,t},$$

$$\varepsilon_{i,t} \big| \Omega_{i,t-1} \approx N(0, h_{i,t}),$$

$$h_{i,t} = \omega + \delta\varepsilon_{i,t-1}^2 + \gamma\varepsilon_{i,t-1}^2 D_{i,t-1} + \theta h_{i,t-1}$$

$R_{i,t}$ denotes the stock *i* daily return on day *t*. $R_{i,t-j}$ denotes the stock *i* daily return on day *t-j*. $DummyMonday_{i,t}$ is a dummy variable set equal to one if it is Monday and equal zero otherwise. $DummyFootballOutcome_{i,t}$ is a dummy variable for trading after the famous football game. In Panel A (Panel B), this football dummy variable is set equal to one if it is a trading day after the Manchester United win (lose) in the game and equal zero otherwise. For Panel C (Panel D), it is set equal to one if it is a trading day after the Liverpool win (lose) in the game and equal zero otherwise. Ω_{t-1} is the information set at time *t-1*. D_{t-1} is a dummy variable that allow good news and bad news to have different impacts on the conditional variance. Where D_{t-1} equal to one if ε_{t-1} is less than zero (bad news), and D_{t-1} equals zero (good news) otherwise. The good news has only δ impact on volatility, while the bad news has a $\delta + \gamma$. The AIC and SIC are utilized for determining the optimal lags of returns. The *t-statistics* are reported in the parentheses below the estimated coefficients.

Panel A: Trading day after the Manchester United win

	α_0	ϕ_1	ϕ_2	ϕ_3	α_1	α_2	ω	δ	γ	θ
Lottery-like	0.0009	0.1059	0.0785	0.0476	-0.0039	-0.0006	0.00004	0.1133	-0.0556	0.9064
	(4.75)	(8.34)	(6.26)	(3.88)	(-8.69)	(-0.77)	(6.66)	(4.11)	(-7.97)	(15.51)
Nonlottery-like	0.0008	0.1062	0.0779	0.0475	-0.0042	0.0014	0.00004	0.1121	-0.0053	0.9068
	(4.33)	(8.35)	(6.21)	(3.87)	(-9.27)	(1.59)	(6.66)	(4.16)	(-7.84)	(15.82)
Other stocks	0.0008	0.1062	0.0709	0.0472	-0.0041	0.0006	0.00003	0.1109	-0.0534	0.9076
	(4.45)	(8.37)	(6.23)	(3.84)	(-9.10)	(0.73)	(6.68)	(4.22)	(-7.83)	(15.66)

Panel B: Trading day after the Manchester United loss

	α_0	ϕ_1	ϕ_2	ϕ_3	α_1	α_2	ω	δ	γ	θ
Lottery-like	0.0007	0.1063	0.0785	0.0476	-0.0041	0.0019	0.00004	0.1113	-0.0537	0.9073
	(4.24)	(8.37)	(6.25)	(3.87)	(-9.27)	(0.98)	(6.67)	(4.21)	(-7.82)	(15.43)
Nonlottery-like	0.0008	0.1060	0.0778	0.0472	-0.0040	0.0016	0.00003	0.1122	-0.0540	0.9067
	(4.29)	(8.35)	(6.20)	(3.85)	(-9.24)	(0.74)	(6.62)	(4.17)	(-7.83)	(14.76)
Other stocks	0.0007	0.1062	0.0779	0.0475	-0.0042	0.0034	0.00004	0.1123	-0.0540	0.9066
	(4.23)	(8.36)	(6.21)	(3.87)	(-9.30)	(1.47)	(6.65)	(4.07)	(-7.80)	(14.67)

Table C3 (Continued)
Gambling Seasonality and the Football Effects

Panel C: Trading day after the Liverpool win

	α_0	$\varnothing_1$	$\varnothing_2$	$\varnothing_3$	α_1	α_2	ω	δ	γ	θ
Lottery-like	0.0008	0.1061	0.0783	0.0478	-0.0041	0.0007	0.00004	0.1120	-0.0545	0.9071
	(4.42)	(8.35)	(6.23)	(3.89)	(-9.10)	(0.79)	(6.68)	(4.15)	(-7.88)	(15.24)
Nonlottery-like	0.0008	0.1063	0.0779	0.0474	-0.0040	0.0008	0.00004	0.1115	-0.0537	0.9072
	(4.43)	(8.37)	(6.22)	(3.86)	(-9.07)	(0.82)	(6.62)	(4.09)	(-7.79)	(15.38)
Other stocks	0.0007	0.1062	0.0780	0.0475	-0.0041	0.0015	0.00003	0.1117	-0.0538	0.9071
	(4.31)	(8.36)	(6.22)	(3.86)	(-9.30)	(1.50)	(6.69)	(4.15)	(-7.81)	(15.88)

Panel D: Trading day after the Liverpool loss

	α_0	$\varnothing_1$	$\varnothing_2$	$\varnothing_3$	α_1	α_2	ω	δ	γ	θ
Lottery-like	0.0008	0.1057	0.0779	0.0479	-0.0039	-0.0011	0.00003	0.1121	-0.0543	0.9072
	(4.44)	(8.32)	(6.21)	(3.90)	(-8.99)	(-0.69)	(6.63)	(4.19)	(-7.87)	(15.72)
Nonlottery-like	0.0007	0.1059	0.0781	0.0475	-0.0042	0.0039	0.00004	0.1123	-0.0541	0.9067
	(4.14)	(8.34)	(6.23)	(3.87)	(-9.44)	(2.36)	(6.64)	(14.16)	(-7.83)	(15.46)
Other stocks	0.0008	0.1062	0.0779	0.0476	-0.0041	0.0013	0.00004	0.1119	-0.0540	0.9071
	(4.25)	(8.36)	(6.22)	(3.87)	(-9.20)	(0.83)	(6.64)	(4.08)	(-7.80)	(15.73)

Table C4
Gambling Seasonality and the Joint Football Effects

This table reports the estimated coefficients of the GJR-GARCH model. In this model, the autoregressive processes are used to correct the autocorrelation in stock returns. The sample period is from January 1999 to December 2008. Specifically, the following GARCH models are estimated;

$$R_{i,t} = \alpha_0 + \sum_{j=1}^{k} \phi_j R_{i,t-j} + \alpha_1 DummyMonday_{i,t} + \alpha_2 DummyJoinFootballOutcome_{i,t} + \varepsilon_{i,t},$$

$$\varepsilon_{i,t} \big| \Omega_{i,t-1} \approx N(0, h_{i,t}),$$

$$h_{i,t} = \omega + \delta \varepsilon^2_{i,t-1} + \gamma \varepsilon^2_{i,t-1} D_{i,t-1} + \theta h_{i,t-1}$$

$R_{i,t}$ denotes the stock *i* daily return on day *t*. $R_{i,t-j}$ denotes the stock *i* daily return on day *t-j*. $DummyMonday_{i,t}$ is a dummy variable set equal to one if it is Monday and equal zero otherwise. $DummyJointFootballOutcome_{i,t}$ is a dummy variable for trading after the famous football game. In Panel A, this football dummy variable is set equal to one if it is a trading day after the Manchester United win and Liverpool team lose and equal zero otherwise. In Panel B, it is set equal to one if it is a trading day after the Manchester United loss and Liverpool win and equal zero otherwise. For Panel C (Panel D), the joint dummy variable is set equal to one if it is a trading day that both teams win (lose) in the games and equal zero otherwise. Ω_{t-1} is the information set at time *t-1*. D_{t-1} is a dummy variable that allow good news and bad news to have different impacts on the conditional variance. Where D_{t-1} equal to one if ε_{t-1} is less than zero (bad news), and D_{t-1} equals zero (good news) otherwise. The good news has only δ impact on volatility, while the bad news has a $\delta + \gamma$. The AIC and SIC are utilized for determining the optimal lags of returns. The *t-statistics* are reported in the parentheses below the estimated coefficients.

Panel A: Trading day after the Manchester United win and Liverpool loss

	α_0	$ø_1$	$ø_2$	$ø_3$	α_1	α_2	ω	δ	γ	θ
Lottery-like	0.0015	0.1097	0.0801	0.0491	-0.0040	-0.0003	0.00004	0.1096	-0.052	0.9092
	(7.54)	(8.70)	(6.43)	(4.02)	(-9.12)	(-0.15)	(6.63)	(4.24)	(-7.78)	(15.11)
Nonlottery-like	0.0014	0.1099	0.0803	0.0492	-0.0041	0.0042	0.00004	0.1102	-0.0523	0.9088
	(7.50)	(8.72)	(6.44)	(4.03)	(-9.36)	(2.17)	(6.63)	(4.20)	(-7.73)	(15.05)
Other stocks	0.0015	0.1098	0.0802	0.0492	-0.0041	0.0025	0.00003	0.1099	-0.0521	0.9087
	(7.52)	(8.71)	(6.44)	(4.03)	(-9.28)	(1.29)	(6.66)	(4.32)	(-7.78)	(15.30)

Panel B: Trading day after the Manchester United loss and Liverpool win

	α_0	$ø_1$	$ø_2$	$ø_3$	α_1	α_2	ω	δ	γ	θ
Lottery-like	0.0015	0.1107	0.0786	0.0479	-0.0041	0.0059	0.00003	0.1101	-0.0515	0.9086
	(7.53)	(8.78)	(6.33)	(3.92)	(-9.35)	(2.16)	(6.57)	(4.20)	(-7.63)	(15.66)
Nonlottery-like	0.0015	0.1099	0.0801	0.0492	-0.0040	-0.0006	0.00004	0.1095	-0.0519	0.9090
	(7.55)	(8.71)	(6.43)	(4.02)	(-9.15)	(-0.17)	(6.65)	(4.28)	(-7.76)	(15.06)
Other stocks	0.0014	0.1108	0.0799	0.0478	-0.0041	0.0089	0.00004	0.1122	-0.0069	0.9069
	(7.46)	(8.79)	(6.42)	(3.92)	(-9.38)	(2.84)	(6.55)	(3.97)	(-7.72)	(14.10)

Table C4 (Continued)
Gambling Seasonality and the Joint Football Effects

Panel C: Trading day after the Liverpool win and Manchester United win

	α_0	$\varnothing_1$	$\varnothing_2$	$\varnothing_3$	α_1	α_2	ω	δ	γ	θ
Lottery-like	0.0015 (7.55)	0.1097 (8.70)	0.08006 (6.42)	0.0431 (4.04)	-0.0042 (-9.26)	0.0017 (1.37)	0.00004 (6.62)	0.1091 (4.28)	-0.0514 (-7.68)	0.9093 (15.63)
Nonlottery-like	0.0014 (7.52)	0.1102 (8.74)	0.080482 (6.46)	0.0491 (4.01)	-0.0041 (-9.19)	0.0013 (0.98)	0.00004 (6.65)	0.1100 (4.22)	-0.0524 (-7.78)	0.9089 (15.01)
Other stocks	0.0014 (7.52)	0.1097 (8.72)	0.080145 (6.43)	0.0495 (4.05)	-0.0042 (-9.31)	0.0019 (1.45)	0.00003 (6.63)	0.1099 (4.24)	-0.0523 (-7.79)	0.9089 (15.98)

Panel D: Trading day after the Liverpool lose and Manchester United lose

	α_0	$\varnothing_1$	$\varnothing_2$	$\varnothing_3$	α_1	α_2	ω	δ	γ	θ
Lottery-like	0.0015 (7.57)	0.1099 (8.72)	0.0802 (6.43)	0.0492 (4.02)	-0.0040 (-9.15)	-0.0009 (-0.18)	0.00004 (6.61)	0.1097 (4.28)	-0.0522 (-7.78)	0.9089 (15.56)
Nonlottery-like	0.0014 (7.55)	0.1094 (8.68)	0.0800 (6.42)	0.0489 (4.00)	-0.0041 (-9.26)	0.0070 (1.22)	0.00003 (6.62)	0.1094 (4.24)	-0.0517 (-7.74)	0.9093 (15.14)
Other stocks	0.0014 (7.58)	0.1096 (8.70)	0.0798 (6.430)	0.0488 (4.01)	-0.0040 (-9.16)	-0.0010 (-0.17)	0.00004 (6.60)	0.1102 (4.17)	-0.0524 (-7.77)	0.9086 (15.84)

BIOGRAPHY

Atchara Yomsin was born and raised in Bangkok. She graduated in 1992 from Bangkok University with the First Class Honor majoring in Accounting. She earned her Master of Business Administration form Indiana University of Pennsylvania, USA in 1995. Prior to joining the Joint Doctoral Program in Business Administration (JDBA), she taught for several years at Bangkok University and frequently invited as a guess speaker on personal finance issue at various organizations. Atchara has written the personal finance monthly article for Krungthep Thurakij Newspaper since 2005 and has a several pocket books on personal finance.