What happens when gamblers get their hands on money? Lottery-type stocks at the turn of the month.

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Abstract

Lottery-type stocks outperform the rest at the turn of the month. This effect is particularly pronounced among firms located in areas whose demographic profile resembles that of the typical lottery-ticket buyers (i.e. gamblers) and partially driven by the within-month cyclicality of local investors' personal liquidity positions. Consistent with the notion that gambling is associated with inattention, we find underreaction to earnings news issued by lottery-type firms located in areas with many gambling investors. The drift following bad news issued at the turn of the month is partly responsible for the underperformance of lottery-type stocks during non-turn of the month periods.

Keywords: Lottery-type stocks; turn-of-the-month effect; gambling; inattention

JEL codes: G14

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1. Introduction

Very much like state lotteries' tickets, stocks with lottery-like features (i.e., low price and high idiosyncratic volatility and skewness) attract investors who have strong propensity to gamble and tend to be poorer, less educated, urban, catholic, and belong to minority groups (Kumar, 2009). With low income and possibly limited savings, this type of investor typically experiences a great deal of change in his or her personal liquidity position at the turn of a calendar month: availability of investable capital tends to peak at the beginning of the month and reach its lowest level toward the end of the month. Indeed there is evidence that economic activity follows a similar within-month cyclical pattern, with the largest swing in consumption having been observed for lottery sales (Evans and Moore, 2012). Thus, for the gambling-motivated investor who likes lottery stocks, investments are also expected to reach a trough just prior to the end of a calendar month and peak shortly thereafter, i.e. in the first few trading days of the new calendar month. If our conjecture is correct, this pattern would coincide with the well documented turn-of-the-month (hereafter, ToM) anomaly wherein stocks tend to perform better on trading days encompassing the change of a calendar month. Our investigation is focused on the performance of lottery stocks around the turn-of-the month and its interplay with changes in personal liquidity affecting individuals' economic activity. In this paper, we take up the task of examining whether the ToM effect is more significant for lottery-type stocks than for other stocks and whether it can be explained by investors' within-month cycle of personal liquidity.

We hypothesize that the short-term surge in stock returns at the turn of the month would be stronger for lottery-type stocks than for non-lottery-type stocks and that any superior performance of lottery stocks should be more pronounced among stocks in areas that present a closer fit with the demographic profile of the typical lottery investor. Moreover, we posit that the difference in performance between lottery and non-lottery stocks around the turn of a month can be partly attributed to lottery investors' greater susceptibility to changes in personal liquidity that affects economic activity around the same period.

Our analysis utilizes several identification strategies aimed at establishing that any price effects associated with lottery stocks at the turn of the month are indeed a result of monthly cycles in personal liquidity of investors. First, we provide a direct test using the brokerage data from Kumar (2009) showing that liquidity-constrained investors are more likely to buy lottery stocks at the ToM than at other times. We then use the county-level change in mortality at the ToM to proxy for the change in the personal liquidity position of local investors in the county (Evans and Moore (2012)) and show that the ToM effect of lottery stocks is particularly pronounced in areas experiencing the largest change in mortality at the ToM, i.e. the greatest liquidity issues. In order to account for the potential criticism that it is some unobservable characteristic correlated with being "lottery-type" that is driving our ToM results we utilize stock splits to devise a test that is free from identification issues. Specifically, we show that the ToM effect becomes more pronounced for the same stock after the split. Additionally, we also establish a causal link between lottery type stocks' prices and trading by liquidity constrained local investors by using an exogenous shock to local investors' trading. This is achieved by accounting for cases of power outage (see Shive (2013)) that are exogenous events constraining local trading.

Finally, we use the paradigm of lottery type stocks issuing earnings announcements at the turn of the month as a natural experiment that allows a closer look at the way gamblers behave when confronted with important information about the gamble they are about to embark on. We rely on prior evidence that there is a strong association among pathological gambling, attention deficit, and other impulse control disorders such as ADHD (e.g., see Specker *et al* (1995) and Faregh and Derevensky (2011)) and conjecture that when individuals make decisions about high-stakes investments (such as lottery stocks), they tend to use information-processing heuristics that essentially limit the extent to which they incorporate even the information they are actively observing (see, for example, Lacetera, Pope, and Sydnor (2011)). Thus we hypothesize that when lottery investors' are most active (i.e. around the ToM), they underreact to fundamentals-related news (i.e. earnings announcements), giving rise to more pronounced delayed response (post-earnings announcement drift (PEAD)).

2. Background

Gambling is a major commercial activity that has been attracting people fascinated by games of chance for centuries. Individuals' propensity to gamble seems to go beyond the occasional attempt to try out their luck by visiting a casino or by purchasing lottery tickets, and seems to play a major role in investments decisions as well.

For example, as early as 60 years ago, Markowitz (1952) suggested that "generally people avoid symmetric bets" and certain investors could "take large chances of a small loss for a small chance of a large gain." In fact, human aspirations, thoughts, and emotions are the reasons why people still trade in stocks much like the way they buy lottery tickets even though they know it is a negative sum game (Statman, 2002). In a similar vein, Barberis and Huang (2008) show that positively skewed securities can be 'overpriced' and earn negative average excess returns. Conjecturing that people's propensity to gamble might relate to stock market trading, Kumar (2009) investigates the influence of gambling attitudes on stock investment decisions and presents evidence that individual investors' socioeconomic characteristics can affect their investment decisions. His findings suggest that investors who are poor, young, relatively less educated, single men, who live in urban areas and belong to specific minority (African-American and Hispanic) and religious (Catholic) groups invest disproportionately more in stocks that are perceived as gambling devices because the distribution of their payoffs resembles that of lottery tickets, i.e. lottery-type stocks. Doran et al. (2012) provides evidence that while lottery-like options and stocks in the U.S. do not necessarily outperform most of the year, they exhibit higher prices and returns at the start of a calendar year. They attribute this phenomenon to the stronger gambling mentality and increased buying activities of some market participants around the New Year holiday.

There is a considerable body of empirical evidence documenting the ToM effect, labeled an anomaly in the literature because it clearly stands in conflict with the concept of market efficiency. Ariel (1987) reports a cyclical pattern in value-weighted and equally weighted daily stock index returns for the period 1963 - 1981 and names it “monthly effect”, for which he could not provide a sufficient explanation. The pattern consists of higher mean stock returns during the initial few days of a trading month than during days later in the month. Lakonishok and Smidt (1988) refer to the four consecutive trading days that begin with the last trading day of a month, as turn-of-month trading days and find strong ToM stock returns on the Dow Jones Industrial Average index for the period 1897 – 1986. Odgen (1990) provides extra evidence and an explanation for the ToM effect. He proposes and tests a hypothesis that the standardization in the payments system in the United States that leads to a concentration of cash flows at the ToM month contributes, at least in part, to the monthly and January effects. He explains that since the liquid profit position of investors tends to be at its highest level at the turn of each calendar month, the ensuing increase in demand leads to the surge of stock returns at the ToM. Cadsby and Ratner (1992) also study the ToM and pre-holiday effects in international markets. They find that the ToM effect is significant in Canada, the UK, Australia, Switzerland, and West Germany but not significant in Japan, Hong Kong, Italy or France. They conclude that the absence of these effects in certain markets suggests that they may originate from country-specific institutional practices.

A seemingly unrelated, yet as it turns out quite relevant, strand of literature focuses on the within-month cycle of mortality. In the United States, according to Phillips *et al.* (1999), daily mortality counts fluctuate over the course of a calendar month with the number of deaths being 1% above average in the first week of the month and 1% below average in the last week of the preceding month. They speculate that the increased risk of death at the beginning of the month might be associated with behavioral changes (for example, a sudden increase in substance use) during the same period since "money to purchase drugs and alcohol tends to be available at the beginning of the month and is relatively less available (for people with low incomes) at the end of month." Indeed, payments of many types of federal benefits, such as Social Security, welfare, and military benefits, typically occur at the beginning of each month. Evans and Moore (2012) document that a similar within-month cycle exists in people's economic activity and provide suggestive evidence that both mortality and economic activity within-month cycles are linked to changes of personal liquidity over the course of the month. Particularly, people who have low levels of wealth and financial savings (measured by education attainment) also suffer the biggest jump in mortality at the beginning of month. Another interesting finding in their study is that state lottery sales in both Maryland and Ohio lotteries exhibit a within-month cycle and reach a peak in the first week of the month. Since people who purchase state lotteries and people who invest in lottery-type stocks share common characteristics (Kumar (2009)), we conjecture that the demand for lottery-type stocks tends to be the highest at the turn of month when the liquidity position of lottery-type stock investors is at its strongest and that this short-lived price pressure effect could be the driver of higher ToM returns for lottery-type stocks.

The typical lottery-type stock investor could be categorized as less sophisticated and more likely to suffer from information processing constraints associated with limited resources and analytical skills. There is also a fairly large literature that argues that gambling is associated with attention deficit and other similar impulse control disorders such as ADHD (e.g., see Specker *et al* (1995) and Faregh and Derevensky (2011)). In addition, it is quite possible that lottery-type stock investors during the turn of the month will tend to use heuristics that limit the use of important information, as has been observed in the case of people making decisions that involve high stakes (Lacetera, Pope, and Sydnor (2011)). We therefore argue that it is conceivable that lottery investors may underreact to value-relevant information during the turn of the month, when their gambling-motivated demand for lottery stocks peaks. If this conjecture is correct we should observe a subdued immediate reaction to lottery stocks' earnings news issued at the ToM, followed by a more pronounced delayed reaction (i.e. more drift).

Our findings can be summarized as follows. We first document a strong positive relation between lottery-type stocks and ToM stock returns, a result consistent with the notion that investors' propensity to gamble (i.e. lottery-type investments) is a significant contributor to the ToM effect. Lottery-type stocks significantly outperform nonlottery-type stocks by 0.030% in daily stock return on average after controlling for time- and industry- fixed effects, the turn-of-week effect, and firm characteristics. We then confirm that the exaggerated ToM performance of lottery stocks is driven by investors' desire to gamble by showing that the effect is particularly pronounced in areas with an abundance of local investors that fit the lottery stock investor demographic profile. Specifically, our results show that the ToM return performance is not associated with lottery-type stocks themselves, but it is significantly stronger for lottery-type stocks by firms located in areas with many investors typically attracted to investments that resemble gambling. A potential criticism of the lottery-type stocks' ToM effect is that there could be some unobservable characteristic correlated with being "lottery-type" that is affecting our results. In order to account for this possibility of endogeneity, we use stock splits to devise a test that is free of identification issues. Since stock price is one of the criteria for classifying stocks as lottery-type the ToM effect should get stronger for the same stock after a stock split. Indeed we show that this is the case, in particular among stocks located in areas with many investors that fit the profile of "gamblers". To provide a causal link between the activity of local liquidity constrained investors and lottery stocks' performance at the ToM, we examine the instances of power outages that occurred at the ToM as exogenous shocks that constrain trading by local investors. We find that in areas with many lottery-type investors power outages are associated with a significantly lower lottery stocks' ToM effect.

Finally, we link the superior ToM performance of lottery stocks to changes in local investors' personal liquidity positions around the time surrounding the end of a calendar month and the beginning of the next month. This is done by first providing a more direct test of the hypothesis that there is cyclicality in trading behavior of investors who are liquidity constrained and prefer lottery-type stocks. We use household level investments data from a brokerage house covering the 1991-1996 period to show that liquidity-constrained investors buy more lottery-type stocks at the ToM. We then follow (Evans and Moore, 2012) and use county-level change in mortality rate as a proxy for change in personal liquidity position. Our results show that changes in personal liquidity are a driver of lottery-type stocks' ToM effect, especially in areas with greater concentration of local investors with high propensity to gamble on lottery-type stocks.

Our investigation on the reaction of lottery stock investors to earnings news yields additional interesting results. We first uncover a weaker immediate reaction to lottery stocks' earnings news when issued at the turn of the month than all other earnings news. This underreaction is found to be particularly pronounced among firms located in areas where there is an abundance of local investors that fit the profile of lottery ticket buyers. Furthermore we report that the immediate underreaction to earnings news by lottery stocks at the ToM is followed by a stronger post-earnings announcement drift. The results are consistent with the notion that lottery stock investors tend to be distracted at the ToM when they make investments driven by impulse rather than paying attention to fundamentals.

We also examine the non-ToM returns of lottery-type stocks and find that stocks with lottery features no longer outperform the rest of stocks during this period and in fact they perform significantly worse. This poor performance is also likely to be driven by the within-month personal liquidity cycle since we find evidence that returns of lottery-type stocks decrease as the concentration of local lottery investors goes up at the non-ToM period. Moreover, we show that those investors' underreaction to bad earnings news issued at the ToM by lottery-type stocks is also a contributing factor in the subsequent poor performance during the non-ToM period of the month.

In the last part of our analysis, we address the issue of whether our results can be used by practitioners as the basis for investment strategies. We first show that an arbitrage portfolio formed to exploit the within-month cyclicality in lottery stocks' performance outperforms by about 0.068% per day or about 17.1% per year, without considering trading costs. We also demonstrate that the post-earnings announcement drift following earnings announcements issued by lottery stocks at the ToM can be used to devise a simple trading strategy that yields an abnormal return of about 13.9% per year. Although the returns of the aforementioned investment strategies are not adjusted for transactions costs, their sheer magnitude implies that they are meaningful in economic terms.

3. Hypotheses

Lottery-type stocks resemble lottery tickets in terms of their low price, high volatility and high skewness characteristics. Kumar (2009) showed that the average investor with strong propensity to gamble in the stock market shares similar demographic and socioeconomic backgrounds with the typical state lottery players. Evans and Moore (2012) show that state lottery sales in both Maryland and Ohio have a pronounced monthly cycle and are highest in the first week of the month. Other economic activities, including going to shopping mall and watching movies, display similar patterns. They link this monthly economic activity cycle to changing personal liquidity over the course of a month. Considering the fact that there are strong similarities between people who purchase state lotteries and individual investors who have strong preference for lottery-type stocks, we conjecture that lottery stock investors' investment decisions could also be largely affected by their personal liquidity position which can follow a pronounced within-month cyclical pattern. Specifically, we argue that it is possible that there exists a monthly cycle of demand for those stocks with lottery features: individual investors' propensity to invest in lottery-type stocks could reach a trough at the end of a calendar month and peak at the beginning of the next month when investable funds become most available, just like state lottery players drive up lottery sales at the same period of time. Such a pattern of course overlaps with the well-known ToM effect, where stocks tend to enigmatically outperform during the period spanning the last trading day of a month and the first few trading days of the next month. When attempting to explain the anomaly in the equity returns at the turn of month, Odgen (1990) argues that the ToM effect of stock returns is the result of a disproportionate number of payments for many types of federal benefits occurring at the beginning of a calendar month and thereby causing an injection of cash flow to investors and a corresponding surge in demand for stocks. We argue that this mechanism seems to apply particularly well to investors that are typically attracted to lottery stocks, thus leading to the following first hypothesis:

Hypothesis 1: *the turn-of-month effect is more pronounced for lottery-type stocks than for non-lottery-type stocks*.

The second hypothesis is based on our conjecture that lottery type stocks' out-performance around the ToM is not attributed to an innate characteristic of lottery stocks but rather to the surge in demand by individuals that we argue are more likely to invest in this type of stocks.

Hypothesis 2: *the turn-of-the-month effect of lottery stocks is particularly pronounced in firms more likely to attract individuals that prefer lottery-type investments.*

The third hypothesis is designed to address the existence of a personal-liquidity mechanism that we argue could be the driver of the lottery-type stocks' performance around the ToM. As discussed earlier, the typical type of investor that is attracted to lottery stocks is less wealthy and less educated and consequently, more prone to drastic changes in his or her personal liquidity position around the turn of a calendar month. As their personal liquidity rebounds from a trough at the end of the month to a peak at the beginning of the next month, they become more likely to lead a short-term surge in demand for lottery-type investments.

Hypothesis 3: *lottery stocks' propensity to display a strong turn-of-month effect is driven by a change in the personal liquidity position of individuals who are typically attracted to lottery-type investments.*

The last hypothesis deals with the way lottery type stocks' investors respond to relevant information during times when they are more likely to exhibit the strongest level of demand for such stocks. If their inclination to gamble constitutes an impulse that is difficult to control they may be paying less attention to firm value-related news released at the ToM.

Hypothesis 4: *lottery stocks earnings announcements issued at the turn of the month will be met with a weaker (stronger) immediate (delayed) reaction, especially in areas where local investors' demographic profiles resemble those of individuals who are typically attracted to lottery-type investments.*

4. Data and Descriptive Statistics

4.1 Lottery Stocks

We follow Kumar (2009) to define and select our sample of lottery-type stocks. Kumar points out that investors who exhibit gambling behavior in the stock market, are more likely to buy stocks that are "cheap bets", "occasionally generate extreme positive returns", and whose "extreme return events observed in the past are more likely to be repeated". Thus, we classify lottery-type stocks as those with: (i) low stock price, (ii) high idiosyncratic volatility, and (iii) high idiosyncratic skewness.

Stock returns, trading volume, shares outstanding, and share price information are from the Center for Research in Securities Prices (CRSP). The stock price at month *t* is the closing price at the end of month *t*-1. We compute both idiosyncratic volatility and idiosyncratic skewness of each stock at the end of month *t*, based on information from a 6-month window prior to month *t* (month *t*-6 to *t*-1). For idiosyncratic volatility, we follow Kumar (2009) and Ang et al. (2006), and calculate the following equation:

$$idiovol_{i,t} = \sigma_{i,t}^2 \; = \frac{1}{D(t)} \sum_{d \in T(t)} \varepsilon_{i,d}^2 \tag{1}$$

where $T(t)$ denotes the set of trading days, $D(t)$ denotes the number of days in this set, $\varepsilon_{i,d}$ is the residual on trading day *d* for firm *i* estimated from the four-factor model (Fama and French (1993); Carhart(1997)) using daily stock return time series over $T(t)$. $\sigma^2_{i,t}$ is the variance of the regression residuals over $T(t)$. For idiosyncratic skewness, we follow Harvey and Siddique (2000) and Kumar (2009), and calculate the following equation:

$$idioskew_{i,t} = \frac{1}{D(t)} \; \frac{\sum_{d \in T(t)} \varepsilon_{i,d}^3}{\sigma_{i,t}^3} \tag{2}$$

where $T(t)$ denotes the set of trading days, $D(t)$ denotes the number of days in this set, $\varepsilon_{i,d}$ is the residual on trading day *d* for firm *i* obtained by estimating regressions of daily stocks returns on excess market returns and the squared excess market returns time series over $T(t)$. $\sigma_{i,t}$ is the square root of $idiovol_{i,t}$ estimated from Eq. (1).

Our initial sample includes all stocks in the CRSP universe from 1980 to 2010. After we have computed the idiosyncratic volatility and idiosyncratic skewness at month *t* for each stock in the sample, we sort stocks by their stock price, idiosyncratic volatility, and idiosyncratic skewness, respectively. Then we define the stocks that are in the lowest

50th stock price percentile, the highest 50th idiosyncratic volatility percentile, and the highest 50th idiosyncratic skewness percentile as lottery-type stocks. Those stocks belong to none of those three categories are defined as non-lottery type stocks. The remaining stocks in the CRSP universe are classified as other-type. In our final sample, there are 5059 lottery-type stocks and 17,062 number of nonlottery-type and other-type stocks. To indicate the status of stocks, we use a dummy variable, *Lottery*, which equals one if the stock is classified as lottery-type and zero otherwise.

4.2 Sample Selection and Variable Measurement

We follow Lakonishok and Smidt (1988) and define ToM trading days as the last trading day of a month and first three trading days of the next month. We obtain the daily returns for all firms over the sample period from 1980 to 2010 from CRSP. We control for several firm characteristics in our regression analysis. We measure firm size by the fiscal quarter-end share price times the number of shares outstanding, book-to-market ratio by fiscal quarter-end firm's book value of common equity divided by firm's size, volume turnover by daily trading volume divided by the number of shares outstanding, and firm leverage by fiscal quarter-end firm's book value of debt divided by book value of total assets. In order to control for the "turn-of-week" effect, we include a dummy variable, *Weekend*, which equals one if the four-day ToM period also includes a turn of week. Our analysis also accounts for several county-level variables that characterize local investors' demographic profile. If individuals exhibit local bias, i.e., tend to invest disproportionately in local firms (see, for example, Seasholes and Zhu (2010) among many others), then local investors that fit the profile of a lottery-type stock investor will show preference for local lottery-type stocks. According to Kumar (2009), the typical lottery-type stock investor is more likely to have low levels of income and education, live in urban areas, be Catholic and belong to African-American or Hispanic minority groups. We measure the likelihood that the average local investor fits the profile of a lottery-type stock investor by aggregating the information of six variables into an index, which we label as *Lottery-Type Stock Local Investor* index (*LSLI-Index*). The variables used to construct *LSLI-Index* are: *Urban, Catho/Prot, Education, Income, AfriWhi*, and *InstiOwn. Urban* is a dummy variable, which equals one if the firm's headquarter is located within 100 miles of one of the ten largest metropolitan areas of the U.S. according to the census, and zero otherwise. We follow a number of papers, including Coval and Moskowitz (1999) and Seasholes and Zhu (2010), and use headquarter locations, obtained from Compustat, as a proxy for firm locations. To capture the religiosity of investors, we obtain the religious profile data of all U.S counties from the Association of Religion Data Archives (ARDA) and calculate the ratio of Catholics population to Protestants population (*Catho/Prot*) of each county in the U.S. Using the zip code of each firm headquarter, we assign the corresponding county-level religious characteristics to the firm. *Education* is the percentage of residents in a county with a Bachelor's or higher educational degree. *AfriWhi*, is defined as the number of African-Americans over the number of White-Americans in a county. *Income* is the median of annual household income in a county. The three aforementioned variables related to local demographics are constructed at the county level from information extracted from U.S. census and assigned to all firms with headquarters in particular counties. We follow Bartov, et.al (2000) and use institutional ownership (the percentage of shares held by institutions, *InstiOwn*) as a proxy for investor sophistication and an indicator of a lower probability of lottery-type investors. Institutional ownership data are from the Thomson Financial database, which consists of 13F filings reported quarterly to the Securities and Exchange Commission (SEC) for the sample period. The Lottery-Type Stock Local Investor Index is thus designed as follows:

$$LSLI\text{-}Index = \frac{1}{6N}[Rank(Catho/Prot)+Rank(AfrWhi)+Rank(-InstOwn)$$

$$+Rank(-Income)+ Rank(-Education)] + \frac{1}{6}\,Urban \tag{3}$$

where *N* is the total number of observations and *Rank*( ) is a function that returns the rank of the input variable. It is constructed in such a way that each of the six component variables receives equal weight in the index and that counties with high concentration of lottery-type stock investors have larger values of *LSLI-Index*.

Evans and Moore (2012) suggest that the within-month cycle of mortality is positively related to that of people's economic activity and personal liquidity over the month. Moreover, the change in mortality at the turn of the month tends to be largest for people who have the greatest liquidity issues (low levels of income and education). We use the county-level change of mortality at the turn of the month to proxy the change in the personal liquidity position of local investors in the county. Mortality data are from the Multiple Cause of Death data files compiled by Centers for Disease Control and Prevention (CDC). The CDC dataset includes complete daily death counts information for the early part of our sample, i.e. from 1980 till 1988. However, starting with 1989 it does not report daily counts of deaths by date, but instead provides total counts for each month and average count for each day of the week within a month across all counties in the United States. Thus, for the period 1989-2010 our measure of the change of mortality rate (*ΔMortality*) of each county at the turn of month is merely an estimate based on a six-day window that includes the last three days of a month and the first three days of the next month, denoted by *Day*(*i*), *i=-3,-2,-1,1,2,3*. The mortality rate of this county on each day of 6-day ToM window is denoted by *Mor*(*i*), *i=-3,-2,-1,1,2,3*. Since we do not have mortality information by date, we use the average daily mortality rate for that month and in that county for a particular day of the week in the corresponding day of the aforementioned six-day window. For example, if *Day*(*1*) is a Tuesday, then we use the average daily mortality rate on Tuesdays for that month as *Mor*(*1*). The approximated change in mortality rate at the turn of a month for a given county is thus calculated as follows:

$$\Delta Mortality = \{[Mor(1) - Mor(-1)] + [Mor(2) - Mor(-2)] + [Mor(3) - Mor(-3)]\} \qquad (4)$$

As we did with all other county-level variables, we then assign the appropriate county-level change in mortality rate to all firms with headquarters' zip code within a particular county.

The data selection process described in this section generates a final sample of 4,880,471 firm-ToM trading day observations over the period 1980-2010. Brief definitions and a list of data sources for each variable can be found in Appendix A.

4.4 Descriptive Statistics

Table 1 Panel A presents a general comparison of several stock characteristics between lottery and all other (non-lottery and other-type) stocks. By definition, lottery-type stocks exhibit very different characteristics than the rest of the stocks in terms of stock price, idiosyncratic volatility and idiosyncratic skewness. Consistent with Kumar (2009), our sample's lottery-type stocks are also, on average, smaller, younger, and with higher book-to-market ratio, poorer performance, and less analyst coverage.

Table 1 Panel B displays the descriptive statistics of variables used in empirical analysis for the lottery-type subsample and for the subsample containing the rest of the stocks. Also reported are the mean differences and corresponding t-statistics. The average daily stock return on ToM days, our main variable of interest, is significantly higher for lottery-type stocks (0.302%) compared to the rest of the stocks (0.210%). This is quite interesting considering the fact that lottery-type stocks are typically poor performers (Kumar (2009)) in the long run. Consistent with Kumar (2009), lottery-type stocks in our sample attract less sophisticated investors as evidenced by their lower level of institutional ownership compared to those of the rest of the CRSP universe. Also, firms whose stocks are categorized as lottery-type are located in counties with greater concentration of individuals that fit the profile of the typical lottery ticket buyer – our proxy for lottery stock investor. In particular, counties with more lottery stocks are generally located in urban areas, have greater proportion of Catholics and minorities, and lower levels of household income and education attainment. In addition, we observe that lottery stocks tend to be located in areas with larger difference in mortality rate between the last three days of a month and the first three days of the next month, consistent with the notion that changes in the personal liquidity position of the average local investor are more likely to occur in counties where lottery type stocks are headquartered.

[Please insert Table 1 here]

5. Empirical Results

5.1 Univariate Test

We test the null hypothesis that the mean difference in returns on ToM trading days between lottery-type stocks and the remaining stocks is zero by estimating the following univariate regression model:

$$\mathrm{Ret}_{i,t} = \beta_0 + \beta_1 \, Lottery_{i,t} + \varepsilon_{i,t} \tag{5}$$

where $\mathrm{Ret}_{i,t}$ is stock return measured at turn-of-month day t for stock i; $Lottery_{i,t}$ is a dummy variable which equals one if stock i is categorized as lottery-type stock at t and zero otherwise. $\varepsilon_{i,t}$ is a zero mean, random disturbance term. Since the sample is comprised of panel data from 1980 to 2010, we adjust standard errors for correlation across firms using cluster robust standard errors at firm level for all the regressions in this paper.

Table 2 Column 1 reports the ordinary least-squares (OLS) regression results estimating Eq. (5). In Column 1, we show that the ToM effect is more pronounced for the lottery-type stocks than the rest of stocks in the stock market. The coefficient estimate of *Lottery* is positive and significant at the 1% level, suggesting that lottery-type stocks on average have higher ToM returns than those of non-lottery-type and other-type stocks. The magnitude of the coefficient estimate of *Lottery* is 0.093, indicating that lottery-type stocks on average have 0.093% higher daily returns. Considering the average daily return for the rest of the stocks in the CRSP universe (i.e., non-lottery-type and other-type stocks) on ToM trading days is 0.210%, the result is economically significant as well.

[Please insert Table 2 here]

5.2 Multivariate Tests of the Lottery-type Stocks' ToM Effect

In this sub-section we analyze the relation between type of stocks and ToM stock returns in a multivariate regression framework. We conduct a series of multivariate tests to ensure that the relation between lottery stocks and ToM stock returns is not driven by time- or industry-invariant variables related to firms, or by firm characteristics.

We first control for time and industry fixed effects without adding firm characteristics variables. Year and month dummies are included to reduce omitted variable bias caused by those unobservable factors that are time-invariant. Similarly, industry dummies are included to control the unobservable industry characteristics that can bias the results. Specifically, we estimate the following OLS regression:

$$\text{Ret}_{i,t} = \beta_0 + \beta_1 \text{Lottery}_{i,t} + \sum \textit{time dummies} + \sum \textit{Industries dummies} + \varepsilon_{i,t} \tag{6}$$

Table 2 Column 2 reports the OLS regression results estimating Eq.(6). The coefficient estimate of *Lottery* remains positive and significant at the 1% level, suggesting that our result remains robust even after the addition of those time- and industry- invariant variables.

The existing body of evidence in the literature shows a weekly anomaly in stock returns around the world: stock markets exhibit positive daily returns on Fridays and an opposite pattern on Mondays (Dubois and Louvet (1996)). To alleviate the concern that ToM stocks returns might be partly driven by the turn-of-week effect, we include a dummy variable *Weekend* in our regression, which equals one if the four ToM trading days interval includes a weekend and zero otherwise. Moreover, to further test the robustness of the more pronounced ToM effect of lottery stocks, we include firm characteristics, such as firm size, book-to-market ratio, volume turnover and firm leverage, in our regression too. Specifically, we estimate the following OLS regression:

$$\text{Ret}_{i,t} = \beta_0 + \beta_1 \text{Lottery}_{i,t} + \beta_2 \text{Weekend} + \beta_3 \text{Log(Size)}_{i,t} + \beta_4 \text{Log(BM)}_{i,t} + \beta_5 \text{Turnover}_{i,t} + \beta_6 \text{Leverage}_{i,t} + \sum \textit{time dummies} + \sum \textit{Industries dummies} + \varepsilon_{i,t} \quad (7)$$

Table 2, Column 2 through Column 4 report the OLS regression results when we control for turn-of-week effect, firm characteristics, and both, respectively. Although there is a small drop in its magnitude, the coefficient estimate of *Lottery* remains positive and significant at the 1% level. Thus, the results in Table 2 provide support for our first hypothesis that lottery stocks display a more pronounced ToM effect. Also, the results show that firms with smaller size, larger market-to-book ratio, larger trading volume turnover, and higher leverage tend to generate stronger ToM stock returns on average. Considering that the aforementioned firm characteristics are much in line with the general characteristics of lottery-type stocks reported in Kumar (2009), our results suggest that the strong ToM effect of lottery-type stocks is not likely to be driven by those firm features themselves. In the next section we will take a closer look at the mechanism of this positive relationship between lottery stocks and ToM effect.

5.3 Lottery stocks' ToM effect and Local Investors Demographic Profile

Why do stocks with lottery features outperform the rest of the market during the turn of month, while they tend to perform poorly in the long run? This section provides an investigation of the hypothesis that local investors' preference for lottery type stocks could be the driver of the anomaly in lottery stock returns at the turn of month.

Given the fact that individuals' equity investments are characterized by bias toward stocks of firms located nearby (Coval and Moskowitz (1999)), lottery-type stocks' strong performance at the turn of month could simply be driven by a sharp increase in demand from local investors. According to Kumar (2009), lottery-type stocks and state lottery players attract quite similar groups of people. Specifically, individual investors who have low levels of income and education, are less sophisticated, belong to ethnic minority groups , are Catholics, and live in urban areas, fit the typical profile of investors who have strong preference for stocks with lottery features. Thus, we expect that lottery-type stocks should experience even higher returns at the turn of month when they are located in areas with many local investors that fit the profile of a lottery ticket buyer.

To test this prediction of our second hypothesis, we estimate a model like the one found in Column 4 of Table 2, with the addition of variables that are indicative of strong presence of lottery-type local investors as well as their interactions with *Lottery*. These variables are *Catho/Prot, Urban, Income, Education, AfriWhi,* and *InstOwn.* Each one of these variables captures a different demographic characteristic of the county-level concentration of local lottery-stock investors as reported in Kumar (2009). The last variable, *InstOwn*, is added to account for the likelihood that stock pricing is more likely to be affected by local individual investors in the absence of sizeable institutional ownership. To assess the combined effect of these measures, we also create an index (*LSLI-Index*) that comprises all six measures and is used as a proxy for the concentration of local lottery-type stocks investors. As discussed in detail in Section 4.2, the *LSLI-Index* is constructed in such a way that each of six indicator variables receives equal weight in the index and that counties with high concentration of lottery-type stock local investors have larger values of *LSLI-Index*.

Collectively, the OLS regression results, reported in Table 3, provide support for the second hypothesis and are in line with the notion that the superior performance of lottery stocks around the turn-of-the-month occurs when there is a sizeable presence of local lottery-type investors. In Column 1, we test the effect of *InstOwn* on ToM stock returns. The coefficient estimate of *InstOwn* is negative and significant, indicating that low institutional ownership is associated with better stock performance at the turn of month. More importantly, we observe that the interaction term *Lottery* * *InstOwn* is negative and significant, suggesting that the aforementioned negative association between institutional ownership and ToM return performance is more pronounced among lottery stocks. This result provides support to our argument that lottery-type stocks with lower institutional ownership attract more lottery-type investors and consequently they experience a higher demand-driven price hike and corresponding surge in return at the turn of the month. In the models shown in Column 2 through Column 6, we examine the effect of other indicators of concentration of local investors with strong propensity to gamble, on the ToM stock returns and find similar results: the ToM returns of lottery-type stocks are significantly influenced by the concentration of lottery-type stock local investors in a positive way: lottery-type stocks have higher ToM returns when the firm's headquarter is located in an urban county, or in a county with high proportion of Catholics, or lower annual household income, or lower percentage of college education attainment, or larger African American to White American ratio. In Column 7 we also use the *LSLI-Index*, an aggregate measure of the lottery-type local investor concentration, and find our result still holds. Moreover, as the results in Table 3 show, the inclusion of these lottery-type stock local investor indicator variables in our regression causes the strong positive relation between *Lottery* and ToM returns to disappear. In fact, the *Lottery* coefficient becomes insignificant in all but two models, where it is marginally significant at the 10%-level. This evidence is consistent with the view that lottery-type stocks by themselves are not the reason of their stronger ToM effect.

[Please insert Table 3 here]

5.3. Possible Explanations

In this subsection we provide tests that are free of identification issues and aimed at providing evidence that alleviates concerns about alternative explanations based on the potential for endogeneity.

5.3.1 Lottery-type Stocks' ToM Effect after Stock Splits

In the first test, we consider an exogenous shock to stock price, i.e., stock split, and test whether this decrease in stock price will increase the ToM effect of lottery-type stocks. The reason that we focus on the event of stock split is that a stock that experiences a decrease in price, say, from $20 to $10, will attract more lottery-type investors after the split, since a low stock price is one of the criteria for being a lottery type-stock. This test can alleviate the concern that some unobservable characteristic correlated with being 'lottery-type' that is driving our main results.

The stock splits' data are from CRSP. We consider all stocks that have Factor to Adjust Prices variable with values greater than or equal to 2-for-1, so that there is a substantial decrease in stock price after the split. To be qualified as a stock split event, the stock needs to have return data available over the 12-month period before the split and over the 12-month period after the split. The final split sample contains 3,075 events.

To examine the effect of stock splits on ToM effect, we perform the test separately for the following two cases: 1) firms that were lottery-type stocks in terms of idiosyncratic volatility and skewness but not in terms of price prior to the stock split, and 2) firms that were lottery-type prior to the stock split, and remained lottery type after the stock split. If the ToM effect is truly driven by the demand of local "gamblers", we would expect the effect to be stronger after the stock split for both cases since lower stock prices should render these stocks more attractive to lottery stock investors. The regression model follows the specification of Eq.(7), except that we replace the main variable of interest with a *Split* dummy, which equals one for all trading days after the stock split and zero for all days prior to the stock split:

$$\text{Ret}_{i,t} = \beta_0 + \beta_1 \text{Split}_{i,t} + \beta_2\text{Weekend} + \beta_3\text{Log(Size)}_{i,t} + \beta_4\text{Log(BM)}_{i,t} + \beta_5 \text{Turnover}_{i,t} + \beta_6 \text{Leverage}_{i,t} + \sum \textit{time dummies} + \sum \textit{Industries dummies} + \varepsilon_{i,t} \quad (8)$$

The first three columns of Table 4 report the regression results estimating Eq. (8), for firms that were lottery-type stocks in terms of idiosyncratic volatility and skewness but not in terms of price prior to the stock split. In the full sample test, the coefficient of *Split* is positive and significant at the 5% level, suggesting that ToM effect actually goes up for those stocks that experience a stock split on average. In the subsamples' test the coefficient of *Split* is positive and significant in the highest *LSLI-Index* tercile group but it becomes insignificant in the lowest *LSLI-Index* tercile group. This result is in line with our prediction that the demand for stocks of firms located in areas with high concentration of lottery-type stock local investors will increase when there is a decrease in stock price while stocks of firms located in areas with low concentration of lottery-type stock local investors are unlikely to be affected.

The last three columns of Table 4 reports the regression results estimating Eq. (8), for firms that were lottery-type prior to the stock split, and remained lottery type after the stock split. Once, again, if a lower stock price is one of the features that attract local investors with high propensity for gambling, a stock split should generate more demand for lottery-type stocks and thus a higher ToM effect. The results support our prediction. The coefficients of *Split* are positive and significant in all three samples, suggesting that ToM effect typically goes up for lottery-type stocks after split. Using stock split as an exogenous shock to stock price, the test presented in Table 4 provides evidence that it is the demand for lottery-type stocks and not some unobservable characteristic that drives such stocks' performance at the ToM.

[Please insert Table 4 here]

5.3.2 Lottery-type Stocks' ToM Effect during Power Outages

In this test, we investigate the impact of local trading on lottery stocks' ToM effect by accounting for an exogenous shock that constraints local trading. We follow Shive (2012) and utilize the cases of large power outages as exogenous shocks. Shive (2012) finds that local trading is adversely affected by large power outages in the U.S., with turnover of stocks in the affected areas dropping significantly. If our conjecture that the more pronounced ToM effect of lottery-type stocks is driven by higher demand by local investors with propensity to gamble is correct, then we such observe a more attenuated ToM effect in areas experiencing during power outages because local trading would be constrained.

The power outage data are from the Electric Power Monthly provided by the Energy Information Administration. It reports detailed data on power outages in the U.S. since 2002 such as the beginning and end date of the disturbance, and the area affected, etc. We follow Shive (2012) and define ‘‘outage period’’ as the first full business day of the outage. To be included in the sample, a power outage needs to affect 100,000 customers or more with a specified blackout area. To examine whether the ToM effect of lottery-type stocks becomes weaker when local trading is constrained by a power outage, we estimate a model like the one found in Column 4 of Table 2, with the addition of an *Outage* indicator as well as its interactions with the *Lottery* indicator. *Outage* identifies the potential effect of power outage on local trading and it equals one if the firm is located in the blackout area, and zero otherwise. Our sample period for this test spans the 2002-2010 period only, because power outage data are available starting in 2002.

Table 5 reports the regression results. In Column 1, the coefficient estimate of main variable of interest, *Outage*Lottery* is not significant, indicating that the power outage does not affect ToM stock returns by constraining local trading on average. However, the results in the *LSLI-Index* terciles' subsamples tests support our argument that demand by lottery type investors is responsible for the surge in lottery stocks' performance at the ToM. The coefficient of *Outage*Lottery* is negative and significant in the highest *LSLI-Index* tercile group, suggesting that power outage, by impeding local trading, has an negative impact on the ToM performance of lottery-type stocks in areas with high concentration of investors that like to gamble. This effect of constraint on local trading becomes insignificant as we move to the lowest-*LSLI-Index* tercile regression.

[Please insert Table 5 here]

5.4. Monthly Cycles in Personal liquidity and Lottery Stocks' ToM Effect

Since the liquidity position of people with limited income and wealth deteriorates towards the end of month and recovers at the beginning of the next month, we posit that lottery type stocks' superior performance could be driven by a surge in demand associated with changes in personal liquidity of lottery stock investors. In particular, we argue that investors' ability and desire to gamble in the stock market change through the month and tend to reach a peak at the turn of month when their personal liquidity position experiences a sharp change, going from worst to best.

To properly test the aforementioned hypothesis, we need to cleanly identify that the price effects we showed are indeed a result of monthly cycles in personal liquidity of investors. The evidence so far can be interpreted as suggesting that the ToM effect of lottery-type stocks could be linked with the (monthly) cyclicality of local investors' liquidity positions. In this section, we provide a couple of identification tests to establish a direct link between the cyclicality of lottery stock investors' personal liquidity positions and lottery-type stocks' performance at the ToM.

5.4.1 Demand for Lottery-type Stocks at ToM

We start with a direct test of whether there is cyclicality in trading behavior of investors who are liquidity constrained and prefer to hold lottery-type stocks. We use the trading data of investors from a large discount brokerage firm on the investments of 77,995 households from 1991 through 1996 (see Barber and Odean (2000, 2001) for detailed description of retail investor database). We follow Kumar (2009) and test the null hypothesis that liquidity-constrained investors buy more lottery-type stocks at the ToM, but not at other times, by estimating the following regression model:

$$EBSI_t = \beta_0 + \beta_1 ToM + \beta_2 UNEMP_m + \beta_3\ UEI_m + \beta_4\ MP_m + \beta_5\ RP_m + \beta_6\ TS_m + \varepsilon_{i,t} \qquad (8)$$

The dependent variable is the excess buy-sell imbalance (EBSI) on day t of a given month. It is defined as *EBSIt =LotBSIt −OthBSIt*, where *LotBSIt*, is the day t buy–sell imbalance of a portfolio of lottery stocks, and *OthBSIt* is the day t buy–sell imbalance of a portfolio that contains the other remaining stocks. We use the buy and sell volume of each investor and construct the buy–sell imbalance (*BSI*) of portfolio *p* on day *t* as $BSI_{p,t} = \frac{100}{Npt} \sum_{1}^{Npt} BSI$. The *BSI* for stock *i* on day *t* is defined as $BSI_{i,t} = \frac{(VBi,t-VSi,t)}{(VBi,t+VSi,t)}$, where $VB_{i,t}$ is the buy volume for stock *i* on day *t*, $VS_{i,t}$ is the sell volume for stock *i* on day *t.* The main independent variable is ToM, which is an indicator variable that equals one if the trading day is at ToM and zero otherwise. Control variables are monthly based and include: *UNEMPm*, the U.S. unemployment rate in month m; *UEIm*, the unexpected inflation in month m; *MPm*, the monthly growth in industrial production; *RPm* is the monthly risk premium; *TSm*, the term spread.

Table 6 presents the time series regression estimating Eq. (8). The results show that although the individual investors do not exhibit a significant cyclicality in demand for lottery-type stocks at ToM in general, those who live in areas with high concentration of lottery-type local investors do: the ToM dummy’s coefficient is not significant in the full sample test after controlling for macroeconomics variables, but it becomes positive and significant in model estimated using the subsample of the highest *LSLI-Index* tercile group. This result confirms that the demand for lottery-type stocks exhibits a certain monthly cyclicality and is higher at ToM for liquidity-constrained investors.

[Please insert Table 6 here]

5.4.2 ToM stock returns and change in local lottery-type investors' personal liquidity positions

Our second indentification strategy involves devising a measure of personal liquidity changes. As suggested by Evans and Moore (2012), a within-month cycle of a range of economic activities generated by changes in personal liquidity is reflected in a similar pattern of changes in mortality rate, with the largest peak-to-trough fluctuations experienced around the turn of a month. Thus, we consider county-level change in mortality at the turn of month as a proxy for the change in personal liquidity of local investors and argue that lottery stocks' ToM effect should be more pronounced in counties with large changes in mortality around the ToM.

In Table 7 we regress *ΔMortality* and its interaction with *Lottery* on ToM stock returns, using the same control variables as in the model shown in Table 2, Column 4. Recall that *ΔMortality* is accurately measured for the earlier part of our sample (1980-1988) when complete death rate information is available on a daily basis, but only approximated for all years thereafter (1989-2010). Accordingly, and to ensure that results are not driven by measurement error associated with the approximate measure, the model is estimated separately for the subsamples consisting of the 1980-1988 and the 1989-2004 periods. Indeed, we obtain similar results across the two sub-period tests. The coefficient of the main variable of interest, *ΔMortality* Lottery*, is positive and significant in the full sample regressions (see columns 1 and 5), indicating that lottery-type stocks' performance at the ToM is stronger in counties where there was a large change in mortality at the turn of month than in counties where there was only a small change in mortality over the same period: an evidence that supports our argument that the change of personal liquidity of local investors at the turn of month is at least partly accountable for the significant surge in returns of lottery-type stocks. The results in the *LSLI-Index* terciles' subsamples tests provide further insight and strengthen our argument that demand by lottery type investors is responsible for the surge in lottery stocks' performance at ToM. The coefficient of *ΔMortality* Lottery* is insignificant in the lowest *LSLI-Index* tercile group, i.e. among firms located in areas with least likelihood of existence of lottery-type stock local investors. However, it becomes more positive and significant as we move to the medium- and highest- *LSLI-Index* tercile regressions: the impact of change of personal liquidity on lottery-type stock ToM returns increases with the concentration of lottery-type local investors. This is in line with our expectations and indicates that the channel through which the change in personal liquidity affects lottery stocks' ToM returns cannot exist in the absence of a critical mass of local investors with high propensity for gambling.

[Please insert Table 7 here]

5.5 Earnings Announcements at ToM

Having established the importance of local retail investors who like to gamble for the performance of lottery stocks at the ToM, we turn our attention to the issue of whether such investors' capacity to process value-relevant information is compromised around the ToM. In this subsection, we investigate immediate and delayed price reactions to earning announcements issued during the ToM period by both lottery-type stocks and the rest of stocks. If lottery-type investors' propensity to gamble in lottery stocks is coupled with attention deficit as is often the case with different types of impulse control disorders, then they may be paying less attention to fundamentals and value-relevant news when their demand for lottery stocks is at its peak, i.e. at the ToM. Thus, we expect that in that case they will underreact to earnings announcements by lottery-type firms issued at the ToM.

While prior studies have shown that frictions in the financial markets can prevent or delay the incorporation of relevant information into prices (see Ball and Brown (1968), Bernard and Thomas (1990), Bhushan (1994), Chordia and Shivakumar (2006)), our focus is on the difference of immediate and delayed price reactions to ToM earnings news between stocks with lottery features and the rest of stocks in the market. According to Bartov et al. (2000), institutional holdings, as a proxy for investor sophistication, are negatively correlated with the observed post-announcement abnormal returns. Thus, if lottery-type stock investors are on average less sophisticated and more subject to judgment biases, they may tend to react more slowly to earnings news compared to sophisticated investors. This underreaction would manifest itself in a weaker immediate price reaction of lottery stocks to earnings news and a delay in the incorporation of earnings information leading to a stronger drift in the direction of an earnings surprise (i.e., stronger PEAD).

We obtain the quarterly earnings announcements for our sample firms from Institutional Brokers' Estimate System (I/B/E/S) and include in our analysis only those issued at the turn of the month. This process generates 59,598 ToM firm-earnings announcements. We measure earnings surprise as $FE_{i,q} = (E_{i,q} - F_{i,q})/P_{i,q}$, where $E_{i,q}$ is the actual earnings per share announced in quarter q for firm i, $F_{i,q}$ is the median of the most recent forecasts from all individual analysts covering the stock, and $P_{i,q}$ is the stock price of firm i five trading days before the announcement in quarter q. We follow Livnat and Mendenhall (2006) and calculate cumulative abnormal returns (*CARs*) as "the difference between the firm's daily return from CRSP and the daily return on the portfolio of firms with the same size (the market value of equity from June) and book-to-market ratio (from prior December)." *CAR*(0,1) and *CAR*(2,22) are defined for the trading days' windows of (0,1) and (2,22), capturing immediate reaction and delayed response, respectively. We choose a shorter drift window (2, 22) than in other studies because a longer one would overlap with the next ToM event window and therefore might produce contaminated results. We rank announcements into earnings surprise by quintiles and define the bottom quintile (*FE*1) as bad earnings news and the top quintile (*FE*5) as good earnings news. The spread in abnormal returns between earnings surprise quintiles 5 and 1 (*FE*5− *FE*1) measures the magnitude of the stock price response to extreme earnings news; a larger spread indicates that investors have stronger reaction to earnings news on the announcement date.

We report univariate statistics by type of stock (i.e. lottery vs. all others) of immediate and delayed reaction to bad and good earnings surprises that occur at the turn of month in Panel A of Table 8. We also report immediate and delayed reactions to earnings surprises for the highest- and the lowest- *LSLI*-Index tercile subsamples in Panel B. Also reported are the spreads (FE5 –FE1) and the differences in the magnitude of reaction between lottery and all other stocks. Despite the fact that both groups of firms display significant immediate reaction and PEAD, "Lottery-type" stocks display significantly smaller *CAR*(0,1) spread (weaker immediate reaction) and larger *CAR*(2,22) spread (stronger delayed response) than the rest of the firms. Lottery-type stocks have a mean spread of 2.85% in 2-day cumulative announcement returns (*CAR*(0, 1)) whereas for the rest of the firms the mean spread is 3.31%, indicating that immediate reaction is weaker for lottery-type firms than for the rest of firms. Accordingly, we observe a reverse trend in spread with respect to the delayed response: Lottery-type stocks are associated with stronger PEAD and have a mean spread of 3.44% in PEAD (*CAR*(2, 22)) whereas for the rest of the firms the mean spread is 1.99%. The differences in mean spread of both event windows are statistically significant at the 5%- and 10%- levels, respectively.

Panel B reports the univariate statistics of immediate reaction and PEAD for the highest- and the lowest- *LSLI*-Index tercile subsamples. By dividing the sample into two subsamples by terciles of *LSLI*-Index, we investigate whether this weaker immediate reaction and stronger delayed response to earnings announcements by lottery stocks at the turn of month are mainly associated with large concentrations of gamblers in the local area. The results in Panel B support our prediction. The previous results from Panel A only hold for firms located in areas with high concentration of lottery-type stock local investors. In contrast, no clear pattern can be observed when the concentration of lottery-type stock local investors is low. The results provide evidence that the underreaction to earnings news at the turn of month is more pronounced in geographic areas with high concentration of lottery-type investors. In addition, the evidence is consistent with the notion that such investors behave like gamblers, who are considered less sophisticated and pay less attention to firm fundamentals.

[Please insert Table 8 here]

If there is indeed an underreaction to earnings news for lottery-type stocks as suggested by the results in the previous table, we expect that the impact of bad/good news on the ToM stock returns to be less pronounced for lottery-type stocks than the rest of stocks in the market. To analyze this in a multivariate setting, we follow the specification in Table 2, Column 3, except that the dependent variable is the average daily ToM stock return when there is an earnings announcement issued and that we add earnings news indicators (*FE*1 and *FE*5) and their interaction terms with the *Lottery* indicator variable. Specifically, we estimate the following OLS regression:

$$\text{Ret}_{i,t} = \beta_0 + \beta_1 \text{ Lottery}_{i,t} + \beta_2 FE1_{i,t} + \beta_3 \text{Lottery*}FE1_{i,t} + \beta_4 FE5_{i,t} + \beta_5 \text{Lottery*}FE5_{i,t} + \beta_6 \text{ Controls}_{i,t} + \varepsilon_{i,t} \quad (9)$$

Table 9 Column 1 reports the regression estimates for the full sample. The coefficient estimate of *FE*1 (*FE*5) is negative (positive) and significant at the 1% level. This is not surprising because the immediate price reaction to the bad (good) news tends to be negative (positive). The main variables of interest here are *Lottery***FE*1 and *Lottery***FE*5, which examine whether the impact of the immediate reaction to earnings news on the ToM return performance is significantly different between lottery-type stocks and the rest of stocks. The coefficient estimate of *Lottery***FE*1 (*Lottery***FE*5) is positive (negative) and significant, providing extra evidence that the impact of extreme earnings news on the ToM effect is significantly weaker among lottery type stocks, as a result of underreaction to earnings news for lottery-type stocks. Are lottery-type investors responsible for this underreaction? The results in the highest- and the lowest- *LSLI*-Index terciles' subsamples tests, shown in columns 2 and 3, aim to provide further evidence to answer of this question. The coefficient estimate of *Lottery***FE*1 (*Lottery***FE*5) is still positive (negative) and significant in the highest-*LSLI*-Index tercile subsample but not in lowest-*LSLI*-Index tercile subsample, indicating that the underreaction to earnings news issued by lottery-type firms at the ToM is especially pronounced in areas where there is greater likelihood of existence of "gamblers" (i.e., less sophisticated investors paying little attention to fundamentals) while such underreaction seems not to be significant in areas with few "gamblers".

[Please insert Table 9 here]

It is noteworthy that earnings announcement issuances at the turn of month previously shown in Table 5 seem to be heavily skewed toward bad news in the case of "lottery-type" firms, but not so for all other firms issuing earnings at the ToM. For "lottery-type" firms, the number of bad news issued at the turn of month is 3,724 whereas the number of good news issued at the same period is only 3,058. For the rest of firms, the number of good news issued at the turn of month is 8,230 whereas the number of bad news issued at the same period is only 7,564. As we have shown in the previous section, lottery-type stocks perform better during the ToM period than non-lottery-type and other type stocks. Thus, it is possible that management of "lottery-type" firms might be timing the date of bad news announcements to lessen its negative impact on stock price, i.e., they are more likely to issue bad earnings news at the turn of month than those of the rest of firms. We test whether the propensity to issue bad news is different for lottery firms in a multivariate setting by using an ordered *probit* model with the earnings surprise rank quintiles (*FE_QRank*) as the dependent variable, which is an ordinal variable with five possible outcomes, and controlling for other firm characteristics. Again, we perform subsample tests using the same regression model for the top- and bottom- *LSLI-Index* terciles, in order to examine whether the propensity to issue bad news is more pronounced for firms located in areas with high concentration of "gamblers".

Table 10 presents the regression results for the full sample, as well as the top- and bottom- *LSLI-Index* terciles' subsamples. In the full sample test, the coefficient estimate of *Lottery*, which is the main variable of interest, is negative and significant at 10% level, indicating that lottery-type firms are more likely to issue bad news at the ToM. The magnitude of the coefficient is -0.051, suggesting that if use predicted probabilities for *FE_QRank*=1, the probability of a lottery-type firm to issue bad news at the turn of month is 0.180 while the probability of any other firm to issue bad news at the turn of month is 0.141,Once again, the coefficient estimate of *Lottery* remains significant (and negative) only in the highest-*LSLI*-Index tercile subsample, indicating that propensity to issue bad news is especially strong for lottery firms in areas where there is greater likelihood of existence of "gamblers". This finding is also consistent with the notion that lottery firms' management may be strategically choosing to time the issuance of bad news at the ToM when local investors are least attentive of fundamentals-related news. [1]

[Please insert Table 10 here]

[1] Testing this conjecture requires extensive analysis, which we defer to a future study.

5.6 Performance of Lottery-type Stocks on Non-ToM Trading Days

Thus far, we have shown that lottery-type stocks exhibit better performance at turn of the month trading days compared to the rest of stocks in the market and that this more pronounced ToM effect might be attributable to the increased demand by local investors with strong propensity to gamble who also experience sharp changes in their personal liquidity positions over this period. However, several previous studies have shown that there is a negative relation between lottery-type stocks and stock returns in the long run (e.g., Kumar (2009) and Doran et al. (2012)). Consequently, we expect that lottery-type stocks should perform worse than the rest of stocks in the non-ToM periods. Moreover, since the personal liquidity position of lottery-type stock investors, after reaching a peak the beginning of the month, becomes progressively worse until it reaches a low-point at the end of the month (Phillips et al. (1999)), demand for lottery-type stocks should also decline during the same period. Therefore, we also expect lottery-type stocks with headquarters located in the areas with high concentration of investors who like to gamble, to experience more pronounced underperformance during non-ToM periods.

Table 11 Column 1 reports the results of a regression of lottery-type stocks dummy and other controls on non-ToM average daily returns. We follow the specification in Table 2 Column 3, except that we change the dependent variable to the non-ToM average daily returns. We define non-ToM trading days as trading days that are not at the turn of month. The result shows that lottery-type stocks no longer outperform other stocks during the non-ToM period. In fact, they perform significantly worse compared to other stocks: the coefficient estimate of *Lottery* is negative and significant at the 1% level. This result complements the ToM evidence and together these results imply that the strong surge in lottery-type stocks' returns at the turn of month is likely to be a short-lived price pressure effect that disappears with the diminishing investable capital (i.e., with the deterioration of the liquidity position) of investors with propensity to gamble during the non-ToM period.

In Table 11 Column 2, we include the *LSLI-Index* and its interaction with lottery-type stocks dummy in the regression to see whether high concentration of lottery-type stock local investors will adversely impact returns of lottery-type stocks in the non-ToM period. The result supports our prediction. Instead of having a positive coefficient as in the ToM period, the interaction term *Lottery**LSLI-Index* has a negative coefficient and it is significant at the 5% level. As the availability of investable capital diminishes during the non-ToM period, the demand for risky assets such as lottery-type stocks also decreases significantly in areas with greater concentration of investors that fit the profile of "gamblers". Thus, lottery-type stocks located in high *LSLI-Index* areas perform poorly even during non-ToM periods.

In the last three columns we examine the impact of ToM earnings announcement issuance on the succeeding non-ToM stock returns. We have shown that lottery-type firms have a propensity to issue bad news during ToM and there is a stronger PEAD for those stocks, thus it is very likely that the delayed response to bad news contributes to the underperformance of lottery-type stocks in the non-ToM period. Following the model specification in Table 10, *FE*1 and *FE*5 are two indicator variables representing the issuance of bad news and good news in the preceding ToM period, respectively. In Columns 3 – 5, the coefficients of *FE1* (*FE5*) are negative (positive) and significant, indicating that ToM bad (good) news has significant negative (positive) effect on the stock performance in the succeeding non-ToM period. This is not surprising since we have shown there is a significant PEAD after earnings news issued at the ToM and therefore the delayed response to bad (good) news continues to affect stock returns negatively (positively). Of particular interest to us is the coefficient estimate of *Lottery*FE1* (*Lottery*FE5*), which tells us whether the issuance of bad (good) news at the ToM for lottery-type stocks can explain at least part of their poor performance during non-ToM periods. The results in Columns 3 – 5 support this notion. In Column 3, the coefficient estimate of *Lottery*FE1* is negative and significant while the coefficient estimate of *Lottery*FE5* is not significant, indicating that the delayed response to bad earnings news at the turn of month contributes to the poor performance of lottery-type stocks in the succeeding non-ToM period. In the subsample analysis, we find that the results only hold in the top- *LSLI-Index* tercile sample. This is consistent with our previous finding that stocks with lottery features display stronger PEAD in the areas with greater concentration of "gamblers".

[Please insert Table 11 here]

Overall, the evidence we provide in this study is consistent with the view that the performance of lottery-type stocks in areas with high concentration of investors who like to gamble follows the pattern of the within-month personal liquidity cycle of lottery-type stock local investors: they tend to outperform during the high part of the within-month personal liquidity cycle that occurs around the turn of the month and to underperform during the low part of the within-month personal liquidity cycle (i.e. the non-ToM trading days). Moreover, we also find evidence that the delayed response to bad news announced during the ToM contributes to the underperformance of lottery-type stocks in the non-

ToM period and this pattern is especially pronounced in the areas with possibly high concentration of “gamblers”.

5.7 Trading Strategies

In this subsection, we investigate whether two trading strategies designed on our results can be potentially exploitable for practitioners.

We have found that the outperformance of lottery-type stocks at the turn of month seems to be more pronounced in areas where there is high concentration of lottery stock local investors. We also provided evidence that high concentration of this type of investor in an area is associated with an exacerbation of the underperformance of local lottery-type stocks during non-ToM periods. Thus, in our first trading strategy, we consider an arbitrage portfolio formed by taking opposite (long/short) positions in two equally-weighted extreme portfolios: the portfolio of lottery-type stocks in areas with many gamblers (highest tercile of *LSLI-Index*) and the portfolio of non-lottery-type stocks in areas with few gamblers (lowest tercile of *LSLI-Index*). Specifically, the aforementioned zero-net investment portfolio, will consist of a long position in the lottery-type stocks’ portfolio and a short position in the nonlottery-type stocks’ portfolio during the 4 days of the ToM. The long and short positions will then be reversed during other periods, i.e. short the lottery-type portfolio and long the non-lottery portfolio in the non-ToM period of each month. We then estimate the risk-adjusted performance of this arbitrage portfolio using the four-factor model (Fama and French (1993); Carhart (1997)) and daily returns and present the results in Panel A of Table 12.

Column 1 of Panel A reports the coefficient estimates of the time series regression for this trading strategy. The coefficient of the constant term, the portfolio's alpha, is positive and significant at the 5% level with the magnitude of 0.068, indicating that our arbitrage portfolio outperforms on a risk-adjusted basis by 68 basis points on a daily basis or by about 17.3% per year. Although we do not consider any direct trading costs, the magnitude of the gross return indicates that this strategy's yield is economically significant as well. To examine whether the underreaction of lottery-type stocks to earnings announcement news at the turn of month can also be exploited to enhance this investment strategy, we use the same trading strategy except that we exclude those stocks with earnings announcement at the turn of month and report the results in Column 2. There are good reasons that this strategy could potentially generate more profits for our arbitrage portfolio. First, since lottery-type stocks outperform the rest of stocks at the ToM in general, but are also less responsive to good/bad earnings news, going long in the 4 days of the ToM a lottery-type stocks portfolio that does not include stocks issuing earnings announcement during the same period, could be more profitable. Second, since lottery-type stocks underperform the rest of stocks during non-ToM periods and they have more pronounced PEAD, shorting lottery-type stocks portfolio on the succeeding non-ToM without those stocks issuing earnings announcement on ToM could also prove to be more profitable. Finally, since the rest of stocks seem to share opposite characteristics from lottery-type stocks during the ToM and non-ToM periods, we would expect the portfolio with regard to the rest of stocks could also be more profitable. In Column 2, the coefficient estimate of the portfolio's alpha is 0.071 and significant at the 5% level, indicating that our new arbitrage portfolio's abnormal performance is 71 basis points on a daily basis or about 18.1% per year. As expected, this arbitrage portfolio generates more profits compared to the previous one that includes all stocks, even those with earnings announcements issued at the ToM. For the purpose of showing the impact of ToM earnings announcements on the profits of our arbitrage portfolio, we also use the same trading strategy except that we exclude stocks that have any earnings announcement issued during the month, and present the results in Column 3. The magnitude of the coefficient estimate of the portfolio's alpha is 0.062, suggesting that while the exclusion of earnings announcements during the ToM seems to slightly improve the magnitude of our portfolio's risk-adjusted performance, the exclusion of earnings announcement, as a whole, results in lower performance.

The second trading strategy aims at taking advantage of the underreaction of lottery-type stocks to both good news and bad news at the turn of month. Specifically, this trading strategy is established during every ToM period and entails a zero net investment portfolio that consists of a long position in all lottery-type stocks with good news (FE5) and a short position in all lottery-type stocks with bad news (FE1). We then hold each of these stocks in the portfolio for 20 days, i.e. until the next ToM at which point we re-balance the portfolio. Column 1 in Panel B of Table 12 reports the coefficient estimates of the four-factor regression model for the full sample portfolio. The alpha is positive and significant at the 5% level with the magnitude of 0.055, indicating that our arbitrage portfolio's risk-adjusted daily return is 5.5 basis points, which corresponds to about 14.0% per year. We also form the arbitrage portfolios for the areas with high and low concentration of lottery-stock local investors. Since we have shown previously that the underreaction to earnings news is especially pronounced for lottery-type stocks in the areas with high concentration of “gamblers”, we expect our second trading strategy to work in those areas but not necessarily in areas where investors do not display strong gambling preference. Columns 2 and 3 report the coefficient estimates of the four-factor regression model for the subsample portfolios in areas with many (high *LSLI-Index*) and few (low *LSLI-Index*) gamblers, respectively. The alpha estimate is positive and significant with the magnitude of 0.059 in Column 2, while it is not significant in Column 3. The results indicate that while the trading strategy is still profitable for the portfolio that only includes firms located in the high concentration of lottery-stock local investors, it fails to outperform the regression-based benchmark for the portfolio that only includes firms located in areas with few investors that fit the profile of a lottery-type stock investor.

[Please insert Table 12 here]

6. Conclusion

This paper investigates the performance of lottery-type stocks at the turn of the month in the U.S. stock market. In a comprehensive sample covering the period 1980-2010, we classify lottery-type stocks based on three features: high idiosyncratic volatility, high idiosyncratic skewness, and low stock price (see Kumar (2009)). Despite prior studies’ evidence suggesting that, on average, lottery-type stocks exhibit poor performance we find that they outperform all other stocks at the turn of month. Specifically, controlling for the turn-of-week effect and time- and industry- fixed effects, as well as for several firm characteristics, we find a significantly more pronounced ToM effect for lottery-type stocks than all other stocks. We show that this effect is not likely to be driven by characteristics of lottery-type stocks *per se*. ToM returns of lottery-type stocks are significantly stronger when they are located in areas with high concentration of local investors that fit the profile of lottery ticket buyers. More importantly, we show that the ToM effect for lottery type stocks is at least partially driven by the within-month cycle of personal liquidity, which typically is at a low-point toward the end of each calendar month and at a high-point at the beginning of each calendar month. Thus, since the ToM change in personal liquidity position is more pronounced among investors fitting the "gambler" profile of lottery-type stock investors, it may be a driver of lottery stocks outperformance at the ToM.

We also find that lottery-type stocks significantly underperform during non-ToM trading days, especially when they are headquartered in counties with high concentration of lottery-type local investors. This finding, together with that of the lottery-type stocks' ToM-effect, indicate that lottery-type stocks' performance follows a monthly pattern that is in line with the within-month personal liquidity cycle and are consistent with the notion that the predictable nature of lottery stocks performance is rooted in cyclicality of demand by gambling investors, who experience cyclical changes in their personal liquidity positions.

In the last part of the paper we show that investors tend to underreact to earnings announcements issued by lottery stocks at the ToM, consistent with the notion that lottery-type stock investors tend to pay little attention to fundamentals at the ToM. Also, in line with the psychology literature's view that impulse control disorders (such as gambling) are associated with inattention, we show that underreaction to earnings news at ToM occurs exclusively in the case of lottery-type firms located in areas with high concentration of investors whose demographic profile fits that of lottery ticket buyers (i.e. "gamblers").

Our paper makes several contributions to the literature. First, we provide valuable insight into the within-month cyclical behavior of lottery-type stocks and provide a link to the well-known ToM effect as well as to the within month cyclicality of economic activity driven by personal liquidity changes around the ToM. Second, we use demographics to empirically gauge retail investor behavior which helps us understand the behavior and judgment biases of gamblers as it relates to financial investments. This is done using the paradigm of lottery-type stock investors and their reaction to earnings news around the time when they are most likely to gamble (i.e. at the ToM). Third, we provide preliminary evidence in line with the view that corporate managers of lottery-type firms may be timing the issuance of bad earnings news in order to take advantage of an acutely inattentive local investor clientele at the ToM. Finally, our evidence provides the basis for the blueprint of profitable investment strategies that can be used by practitioners.

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Appendix A: Brief Definitions and Sources of Main Variables

Variable	Definition	Source
Panel A: Stock Characteristics		
Idiosyncratic Volatility	Standard deviation of the residual estimates calculated by fitting four factors model	CRSP
Idiosyncratic Skewness	Third moment of the residual obtained by fitting the daily stock returns on a two-factor model	CRSP
Price	End-of-month stock price	CRSP
Past Return	Monthly stock return during the past 12 months	CRSP
Size	End of month share price times the number of shares outstanding	CRSP
BM	End of month firm's book value divided by firm's size	Compustat
Age	Number of years the firm has existed in the CRSP database	CRSP
Analyst	Number of different analysts covering the stock in a given fiscal quarter	I/B/E/S
Panel B:Variables Used in Regressions		
TOM Ret (%)	Daily stock return on TOM trading days in percentage. TOM trading days are defined as the last and first three trading days of the month	CRSP
Non-TOM Ret (%)	Daily stock return on non-TOM trading days in percentage	CRSP
Lottery	A lottery-type stock indicator variable which equals one if the stock is clasified by as lottery-type stock and zero otherwise.	CRSP
Size	Fiscal quarter-end share price times the number of shares outstanding	CRSP
BM	Fiscal quarter-end firm's book value divided by firm's size	Compustat
Leverage	Fiscal quarter-end firm's book value of debt divided by book value of total assets	Compustat
Turnover	Daily trading volume divided by the number of shares outstanding	CRSP
InstOwn	Percentage of total shares outstanding owned by 13F institution	13F
Urban	Equals one if the firm's headquarter is located within 100 miles of one of the ten largest metropolitan areas of the U.S.	U.S. Census
Mortality	Adjusted average of daility mortality rate in the county where the firm is located.	CDC
Catho/Prot	Population of Catholics over the population of Protestants in the county where the firm is located	ARDA
Education	Percentage of residents with a Bachelor's or higher educational degree on county level	U.S. Census
AfriWhi	The number of African-American over number of White American residents on county level	U.S. Census
Income	Median of annual household on county level	U.S. Census
LSLI	Lottery stock local investor Index-"LSLI-index" defined as: 5/6*[1/5*1/N*Rank(Catho/Prot)+Rank(AfrWhi)-Rank(InstOwn)-Rank(Income)-Rank(Education)] + 5/6*Urban Dummy, where N is the total number of observations and Rank() is a function that returns the rank of variable.	U.S. Census, CDC, 13F, ARDA
FE	Earnings surprise rank quintiles which is an ordinal variable with five possible outcomes	I/B/E/S, CRSP, Compustat
FE1	The most negative earnings surprise quintiles (bad news)	I/B/E/S, CRSP, Compustat
FE5	The most positive earnings surprise quintiles (good news)	I/B/E/S, CRSP, Compustat
EBSI	Excess buy-sell imbalance	Brokerage

Split	An indicator variable which equals one for all trading days after the stock split and zero for all days prior to the stock split	CRSP
Outage	An indicator variable which equals one if the firm is located in the blackout area, and zero otherwise.	EIA

Table 1: Stock characteristics and summary statistics

Table 1 Panel A reports the mean monthly stock characteristics of lottery-type stocks and the rest of stocks over the sample period 1980-2010. We define types of stocks at the end of each month using all stocks in the CRSP universe. Stocks that are in the lowest 50th stock price percentile, the highest 50th idiosyncratic volatility percentile, and the highest 50th idiosyncratic skewness percentile at the end of each month are defined as lottery-type stocks. Those stocks belong to none of those three categories are defined as non-lottery type stocks. Those stocks that are neither lottery-type nor nonlottery-type are defined as other-type. Panel B reports the summary statistics of variables used in regressions. Definitions of all variables are listed in Appendix A.

Panel A: Basic characteristics of lottery stocks

Variable	Lottery-Type	Nonlottery-Type and Other-Type
Number of Stocks	5059	17062
Price	5.02	20.78
Idiosyncratic Volatility	30.45	8.48
Idiosyncratic Skewness	1.94	0.21
Past Return (%)	8.77	15.21
Size (in millions)	119.22	1854.79
BM	0.88	0.24
Age (in years)	6.17	15.64
Analyst	2.55	7.46

Panel B: Summary statistics of variables used in regressions

	Lottery-Type						Nonlottery- and Other-Type							
Variable	N	Mean	Std	P25	Median	P75	N	Mean	Std	P25	Median	P75	Diff	T-Stat
ToM Ret(%)	1,069,876	0.302	7.689	-2.564	0	2.465	3,810,595	0.210	3.631	-1.075	0	1.339	0.092	18.86***
Size (in millions)	1,069,876	99.6	341.1	17.2	43.6	113.8	3,810,595	1570.0	5982.4	110.8	385.2	1409.1	-1470.4	-20.76***
BM	1,069,876	0.699	0.665	0.238	0.495	0.896	3,810,595	0.421	0.472	0.213	0.423	0.687	0.272	29.28***
Turnover (%)	1,069,876	0.651	3.599	0.051	0.199	0.568	3,810,595	0.914	23.535	0.094	0.285	0.737	-0.263	-13.23***
Leverage	1,069,876	0.469	0.658	0.241	0.419	0.626	3,810,595	0.549	0.208	0.368	0.519	0.638	-0.079	-10.57***
InstOwn	1,069,876	0.214	0.204	0.056	0.15	0.314	3,810,595	0.501	0.217	0.45	0.626	0.764	-0.287	-19.28***
Urban	1,069,876	0.489	0.5	0	0	1	3,810,595	0.434	0.499	0	0	1	0.055	11.79***
CathoDum	1,069,876	0.475	0.499	0	0	1	3,810,595	0.380	0.485	0	0	1	0.095	17.72***
Catho/Prot	1,069,876	2.515	2.039	0.784	2.007	3.854	3,810,595	2.403	1.917	0.635	1.7	3.729	0.112	15.98***
Income (in 1,000s)	1,069,876	40.172	11.66	41.48	45.33	55.90	3,810,595	50.160	11.51	42.67	49.932	62.5	-9.988	-9.47***
AfriWhi	1,069,876	0.254	0.281	0.057	0.14	0.294	3,810,595	0.193	0.222	0.045	0.113	0.254	0.061	30.01***
Education	1,069,876	34.440	9.456	24.92	28.545	39.12	3,810,595	36.283	9.153	26.98	31.232	40.05	-1.843	-23.04***
ΔMortality (%)	1,069,876	0.0050	0.0257	0.0144	0.0040	0.0062	3,810,595	0.0034	0.0163	0.0029	0.0029	0.0032	0.0016	19.47***

Table 2: Lottery-type stocks and ToM stock returns

Table 2 examines the relation between types of stocks and ToM stock returns. The dependent variable is ToM stock return. The independent variables are lottery-type stock dummy and other control variables, such as firm size, book-to-market ratio, turnover volume and a turn-of-week dummy. Definitions of all variables are listed in Appendix A. In column 2 - 4, both industry - (i.e., the first two-digit SIC code) and time - (year and month) dummies are included, but coefficient estimates are omitted for brevity. Numbers in parentheses are t-statistics calculated using robust standard errors adjusted by heteroskedasticity and clustered at the firm level. ***, **, * indicate a two-tailed test significance level at the 1%, 5% and 10%, respectively.

Dependent Variable	TOM Stock Return (%)			
	(1)	(2)	(3)	(4)
Lottery	0.093***	0.074***	0.041***	0.030***
	(6.20)	(5.01)	(4.20)	(3.21)
Log(Size)			-0.035***	-0.036***
			(-5.20)	(-5.20)
Log(BM)			-0.128***	-0.128***
Turnover			0.533***	0.533***
			(4.81)	(4.7)
Leverage			0.100**	0.100**
			(2.99)	(2.99)
WeekendDummy		0.155***		0.112***
		(8.77)		(8.00)
Constant	0.162***	0.232***	0.101***	0.100***
	(28.27)	(15.11)	(20.25)	(20.22)
Observations	4,880,471	4,880,471	4,880,471	4,880,471
Adj. R-squared	0.001	0.002	0.002	0.002
Time Dummies	No	Yes	Yes	Yes
Industry Dummies	No	Yes	Yes	Yes

Table 3: ToM stock returns and local lottery-type investors

Table 3 examines the relation between types of stocks and ToM stock returns, introducing interaction terms with several variables that characterize local lottery-type investors, i.e., urban dummy, Catholics and Protestant ratio, institutional ownership, income, African Americans to White American ratio, percentage of population who have bachelor's or higher degree, and Lottery Stock Local Investor Index. Definitions of all variables are listed in Appendix A. The base specification replicates Column 4 in Table 2. In all specifications, the set of control variables include firm size, book-to-market ratio, volume turnover, leverage and weekend dummy. Both industry and time dummies are included, but coefficient estimates are omitted for brevity. Numbers in parentheses are t-statistics calculated using robust standard errors adjusted by heteroskedasticity and clustered at the firm level. ***, **, * indicate a two-tailed test significance level at the 1%, 5% and 10%, respectively.

Dependent Variable	ToM Return (%)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lottery	0.021	0.033*	0.034	0.014	0.194	0.171	0.032*
	(1.25)	(1.69)	(0.55)	(0.88)	(0.47)	(0.56)	(1.80)
InstOwn	-0.355***						
	(-4.77)						
Lottery*InstOwn	-0.213***						
	(-4.33)						
Urban Dummy		0.006					
		-0.44					
Lottery*Urban		0.014**					
		(2.22)					
Catho/Prot			0.02				
			(1.37)				
Lottery*Catho/Prot			0.019*				
			(1.90)				
AfriWhi				0.047			
				(1.53)			
Lottery*AfriWhi				0.066**			
				(2.04)			
Log(Income)					-0.002		
					(-0.99)		
Lottery*Log(Income)					-0.079**		
					(-2.09)		
Education						-0.011	
						(-0.13)	
Lottery*Education						-0.044***	
						(-2.83)	
LSLI							0.045
							(0.83)
Lottery * LSLI							0.387**
							(2.33)
Observations	4,880,471	4,880,471	4,880,471	4,880,471	4,880,471	4,880,471	4,880,471
Adj. R-squared	0.007	0.021	0.006	0.005	0.011	0.013	0.005
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Stock Splits and lottery type stocks' ToM effect

This table examines the effect of stock splits on ToM stock returns. In Group 1, we perform the test for firms that were lottery-type stocks in terms of idiosyncratic volatility and skewness but not in terms of price prior to the stock split. In Group 2, we perform the test for firms firms that were lottery-type prior to the stock split, and remained lottery type after the stock split. The regression model follows the specification of Eq.(7), except that we replace the main variable of interest with a Split dummy, which equals one for all trading days after the stock split and zero for all days prior to the stock split. Definitions of all variables are listed in Appendix A. In all specifications, the set of control variables include firm size, book-to-market ratio, volume turnover, leverage and weekend dummy. Both industry and time dummies are included, but coefficient estimates are omitted for brevity. Numbers in parentheses are t-statistics calculated using robust standard errors adjusted by heteroskedasticity and clustered at the firm level. ***, **, * indicate a two-tailed test significance level at the 1%, 5% and 10%, respectively.

Dependent Variable	ToM Stock Return (%)					
	Group 1 (IV, skewness)			Group 2 (lottery stocks before and after splits)		
	Full Sample	T3 (Largest)	T1 (Smallest)	Full Sample	T3 (Largest)	T1 (Smallest)
	(1)	(2)	(3)	(4)	(5)	(6)
Split Dummy	0.009**	0.004*	0.001	0.008*	0.004**	0.003*
	(2.37)	(1.76)	(1.24)	(1.89)	(2.43)	(1.89)
Log(Size)	-0.016***	-0.204***	-0.017***	-0.016***	-0.311**	-0.080
	(-4.67)	(-3.33)	(-4.81)	(-6.81)	(-2.24)	(-0.38)
Log(BM)	0.245**	-0.258***	-0.123***	-0.285***	-0.667**	-0.124***
	(2.09)	(-4.26)	(-6.61)	(-6.62)	(-2.21)	(-6.62)
Turnover	0.321***	0.255**	0.321***	0.936***	0.993	-0.375*
	(3.46)	(2.03)	(3.46)	(3.46)	(0.62)	(-1.88)
Leverage	0.074	-0.011	0.075**	1.555**	2.304**	1.180
	(1.02)	(-0.58)	(2.03)	(2.22)	(2.06)	(1.32)
WeekendDummy	0.204	0.543**	0.243*	0.087	0.243**	0.283*
	(1.21)	(2.24)	(1.87)	(1.21)	(2.31)	(1.90)
Constant	0.012	0.011***	0.015	0.012	0.108***	0.011***
	(0.48)	(4.03)	(0.11)	(0.48)	(10.92)	(4.03)
Observations	2,378,204	725,036	605,252	1,564,067	400,068	685,246
Adj. R-squared	0.005	0.004	0.005	0.010	0.005	0.007
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: The impact of power outages on lottery type stocks' ToM effect

Table 7 examines the effect of power outage in U.S on ToM stock returns. We follow Shive (2012) and define ''outage period'' as the first full business day of the outage. To be included in the sample, a power outage needs to affect 100,000 customers or more with a specified blackout area. The model specification follows Column 4 of Table 2, with the addition of *Outage* indicator as well as its interactions with *Lottery*. *Outage* equals one if the firm is located in the blackout area, and zero otherwise. Definitions of all variables are listed in Appendix A. The base specification replicates Column 4 in Table 2. In all specifications, the set of control variables include firm size, book-to-market ratio, volume turnover, leverage and weekend dummy. Both industry and time dummies are included, but coefficient estimates are omitted for brevity. Numbers in parentheses are t-statistics calculated using robust standard errors adjusted by heteroskedasticity and clustered at the firm level. ***, **, * indicate a two-tailed test significance level at the 1%, 5% and 10%, respectively.

	ToM Return %		
	Full Sample	T3 (Largest)	T1 (Smallest)
	(1)	(2)	(3)
Lottery	0.022**	0.032***	0.013
	(2.13)	(2.80)	(0.45)
Outage Dummy	0.006	-0.003	0.002
	(0.96)	(-1.22)	(0.10)
Lottery*Outage	-0.002	-0.005*	-0.001
	(-0.70)	(-1.84)	(-0.57)
Constant	0.378	0.461*	0.089
	(1.40)	(1.90)	(0.64)
Observations	1,430,253	458,645	424,242
Adj. R-squared	0.013	0.013	0.011
Controls	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes

Table 6: Demand for Lottery Stocks at ToM

Table 4 examines the demand of lottery stocks at the ToM using trading data from a large discount brokerage house. The dependent variable is the excess buy-sell imbalance (*EBSI*) on day *t* of a given month. It is defined as $EBSI_{t,m} = LotBSI_{t,m} - OthBSI_{t,m}$, where $LotBSI_{t,m}$ is the day *t* buy–sell imbalance of a portfolio of lottery stocks in month m, and $OthBSI_{t,m}$ is the day *t* buy–sell imbalance of a portfolio that contains the other remaining stocks in month m. Control variables include: $UNEMP_m$, the U.S. unemployment rate in month *m*; UEI_m, the unexpected inflation in month *m*; $MP_{m,}$ the monthly growth in industrial production; RP_m is the monthly risk premium; TS_m, the term spread. Definitions of all variables are listed in Appendix A.

The buy–sell imbalance (*BSI*) of portfolio *p* on day *t* is defined as $BSI_{p,t} = \frac{100}{Npt} \sum_{1}^{Npt} BSI$, where the *BSI* for stock *i* on day *t* is defined as

$$BSI_{i,t} = \frac{(VBi,t - VSi,t)}{(VBi,t + VSi,t)}$$

$VB_{i,t}$ is the buy volume for stock *i* on day *t*, $VS_{i,t}$ is the sell volume for stock *i* on day *t*

Dependent Variable	Excess buy-sell imbalance of lottery-type stocks				
	Full Sample	Full Sample	Subsample Tests by Terciles of *LSLI-Index*		
			T1 (lowest)	T2	T3 (highest)
	(1)	(2)	(3)	(4)	(5)
ToM dummy	0.154*	0.102	0.090	-0.024	0.092**
	(1.74)	(1.28)	(0.85)	(-0.85)	(2.07)
Lagged UNEMP		0.199**	0.208**	0.107	0.211***
		(2.33)	(2.03)	(0.99)	(2.55)
Lagged UEI		-0.056	0.189	0.967*	0.550
		(-1.23)	(0.24)	(1.83)	(1.04)
Lagged MP		-0.020	-0.182*	-0.030	-0.044
		(-0.77)	(-1.73)	(0.62)	(1.31)
Lagger RP		0.488***	0.134*	0.254***	0.277**
		(5.62)	(1.90)	(2.67)	(1.98)
Lagged TS		-0.256	-0.048	-0.136	-0.287*
		(-1.44)	(-0.77)	(0.89)	(1.80)
Constant	0.138	0.085	0.103	0.104	-0.049
	(0.87)	(1.52)	(1.33)	(1.13)	(-0.32)
Number of Days	1,499	1,499	1,499	1,499	1,499
Adj. R-squared	0.014	0.070	0.088	0.101	0.099

Table 7: ToM stock returns and change in local lottery-type investors' personal liquidity positions

This table examines the effect of change of local lottery-type investors' personal liquidity positions on ToM stock returns. We use county-level change in mortality at the turn of month (*ΔMortality*) as a proxy for the change in personal liquidity of local investors. *ΔMortality* is the mean difference in mortality between the first three days of a month and last three days of the last month. The CDC dataset includes complete daily death counts information for the early part of our sample, i.e. from 1980 till 1988, which allows us to directly measure *ΔMortality*. However, starting with 1989 it does not report daily counts of deaths by date, but instead provides total counts for each month and average count for each day of the week within a month across all counties in the United States. Thus, for the period 1990-2010 *ΔMortality* is approximated following the procedure detailed in Section 3.2. Column 1 reports the full sample test using data from the period when *ΔMortality* needs to be approximated (i.e. from 1989 to 2010). Subsample tests using 1989-2010 observations sorted by different terciles of lottery stock local investor index-"*LSLI-Index*" are performed in Columns 2 to 4. Correspondingly, tests using the 1980-1988 sample for which *ΔMortality* can be measured accurately are performed in Columns 5 to 8. The *LSLI-Index* is defined as: $\frac{1}{6N}$ [Rank(*Catho/Prot*)+Rank(*AfriWhi)*+Rank(-*InstOwn*)+Rank(-*Income*)+Rank(-*Education*)]+ $\frac{1}{6}$*Urban*, where *N* is the total number of observations and Rank( ) is a function that returns the rank of the variable. The base specification replicates Column 1 in Table 3. Definitions of all variables are listed in Appendix A. In all specifications, the set of control variables include firm size, book-to-market ratio, volume turnover, leverage and weekend dummy. Both industry and time dummies are included, but coefficient estimates are omitted for brevity. Numbers in parentheses are t-statistics calculated using robust standard errors adjusted by heteroskedasticity and clustered at the firm level. ***, **, * indicate a two-tailed test significance level at the 1%, 5% and 10%, respectively.

Dependent Variable	TOM Stock Return (%)							
	Full Sample 1989-2010	Subsample Tests by Terciles of *LSLI-Index* 1989-2010			Full Sample 1980-1988	Subsample Tests by Terciles of *LSLI-Index* 1980-1988		
		T1 (lowest)	T2	T3 (highest)		T1 (lowest)	T2	T3 (highest)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lottery	0.027	0.014	0.015	0.024	0.142	0.021	0.019	0.028
	(1.11)	(0.22)	(1.36)	(1.20)	(0.88)	(1.09)	(0.85)	(1.33)
ΔMortality	1.325	1.457	1.784	2.230*	1.245*	0.182	0.945*	1.872
	(1.23)	(0.99)	(1.33)	(1.90)	(1.77)	(0.67)	(1.85)	(1.58)
Lottery * ΔMortality	4.002**	-1.082	2.100*	3.287**	2.471**	0.457	0.856*	2.978**
	(2.34)	(-0.62)	(1.84)	(2.25)	(2.82)	(0.74)	(1.93)	(2.14)
Constant	0.524	-0.103	0.194	0.349	0.032	-0.205	0.104	0.076
	(1.02)	(-0.89)	(1.43)	(0.54)	(1.12)	(-1.23)	(1.47)	(0.56)
Observations	3,478,288	1,291,584	1,067,033	1,119,671	1,401,953	489,741	490,147	422,065
Adj. R-squared	0.012	0.016	0.025	0.017	0.012	0.014	0.028	0.010
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Cumulative abnormal returns of extreme ToM earnings surprise quintiles by types of issuing stocks

This table shows the average 2-day excess announcement-period returns CAR(0,1) and 21-day excess announcement-period returns CAR(2,22) for extreme earnings surprise quintiles (FE5: good news, FE1: bad news) at the turn of month by types of stocks. We measure earnings surprise as $FE_{i,q} = (E_{i,q} - F_{i,q})/P_{i,q}$, where $E_{i,q}$ is the actual earnings per share announced in quarter *q* for firm *i*, $F_{i,q}$ is the median of the most recent forecasts from all individual analysts covering the stock, and $P_{i,q}$ is the stock price of firm *i* five trading days before the announcement in quarter *q*. Day 0 represents the day of earnings announcement in all CAR event window definitions. Cumulative abnormal returns are based on a single-factor market model estimated from day -255 to -46 for each sample firm, using the CRSP value-weighted index. Panel A shows the overall sample results and Panel B shows the subsample results by terciles of *LSLI-Index*. ***, **, * indicate statistically significant at the 1%, 5% and 10%, respectively.

Panel A

	CAR(0,1)			CAR(2,22)		
Type of Stocks	FE1	FE5	FE5-FE1	FE1	FE5	FE5-FE1
Lottery (1)	-1.27%**	1.58%**	2.85%***	-1.64%***	1.88%***	3.44%***
	n=3724	n=3058		n=3724	n=3058	
Nonlottery & Other (2)	-1.34%**	1.97%***	3.31%***	-1.04%**	0.95%**	1.99%***
	n=7564	n=8230		n=7564	n=8230	
Difference (1) - (2)	0.07%	-0.39%	-1.14%**	-0.60%*	0.93%**	1.53%**

Panel B

T3: Highest *LSLI-Index* Tercile

	CAR(0,1)			CAR(2,22)		
Type of Stocks	FE1	FE5	FE5-FE1	FE1	FE5	FE5-FE1
Lottery (1)	-1.33%***	1.82%***	2.45%***	-2.34%***	1.50%***	3.84%***
	n=1228	n=1127		n=1228	n=1127	
Nonlottery & Other (2)	-1.87%***	2.83%***	3.89%***	-1.13%***	0.86%***	1.99%***
	n=2528	n=2629		n=2528	n=2629	
Difference (1) - (2)	0.44%	-1.01%**	-1.44%**	-1.21%**	0.64%	1.85%***

T1: Lowest *LSLI-Index* Tercile

	CAR(0,1)			CAR(2,22)		
Type of Stocks	FE1	FE5	FE5-FE1	FE1	FE5	FE5-FE1
Lottery (1)	-1.60%***	2.04%***	3.64%***	-1.49%**	2.03%***	3.52%***
	n=1298	n=1120		n=1298	n=1120	
Nonlottery & Other (2)	-1.70%***	2.45%***	4.15%***	-1.24%***	1.92%***	3.16%***
	n=2507	n=2685		n=2507	n=2685	
Difference (1) - (2)	0.10%	-0.41%	-0.41%	-0.25%	0.09%	-0.36%

Table 9: Impact of earnings announcement on ToM stock returns

This table examines the impact of earnings announcements issued at the ToM on lottery-type stocks' returns and other stocks' returns at the ToM. The dependent variable is ToM stock returns. We measure earnings surprise as $FE_{i,q} = (E_{i,q} - F_{i,q})/P_{i,q}$, where $E_{i,q}$ is the actual earnings per share announced in quarter q for firm i, $F_{i,q}$ is the median of the most recent forecasts from all individual analysts covering the stock, and $P_{i,q}$ is the stock price of firm i five trading days before the announcement in quarter q. FE5 is a good news indicator variable that takes value of 1 if the earnings surprise ranks in the highest forecast error quintile and zero otherwise. FE1 is a bad news indicator variable that takes value of 1 if the earnings surprise ranks in the lowest forecast error quintile and zero otherwise. Column1 reports the full sample test. Subsample tests are performed from Column 2 and 3 for top- and bottom-"*LSLI-Index*" tercile. Definitions of all other variables are listed in Appendix A. Both industry and time dummies are included, but coefficient estimates are omitted for brevity. Numbers in parentheses are *t*-statistics calculated using robust standard errors adjusted by heteroskedasticity and clustered at the firm level. ***, **, * indicate a two-tailed test significance level at the 1%, 5% and 10%, respectively.

	TOM Returns on EAs		
	Full Sample	T3 (Highest)	T1 (Lowest)
	(1)	(2)	(3)
Lottery	0.144	0.207*	0.074
	(1.58)	(1.78)	(0.36)
Log(Size)	-0.145*	-0.247**	0.147
	(-1.85)	(-2.11)	(0.84)
Log(BM)	-0.373*	-0.221*	-0.265
	(-1.91)	(-1.88)	(-1.36)
Turnover	0.079***	0.057***	0.060***
	(7.72)	(3.45)	(2.13)
Leverage	0.035*	0.044	0.03
	(1.87)	(1.32)	(1.02)
FE5	3.749***	3.511***	2.754**
	(4.33)	(2.99)	(3.41)
Lot*FE5	-1.014*	-0.993**	0.787
	(-1.90)	(-2.31)	(0.99)
FE1	-1.146***	-1.113**	-0.323***
	(-3.77)	(-2.33)	(-2.00)
Lot*FE1	0.434**	0.501**	0.413
	(1.99)	(2.04)	(1.29)
Constant	0.011**	0.015	0.012
	(2.03)	(0.11)	(0.48)
Observations	42,581	13,754	12,231
Adj. R-squared	0.036	0.024	0.086
Industry Dummies	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes

Table 10: Propensity of earnings announcement issuance

This table reports the results of an ordered probit regression of the lottery-type stock indicator on earnings surprise quintiles. The dependent variable is FE_QRank, a rank variable that represents earnings surprise quintiles and takes values between 1 and 5. Specifically, FE_QRank=5 when the forecast error ranks in the highest earnings surprise quintile, i.e. extremely good news. FE_QRank=1when the forecast error value ranks in the lowest earnings surprise quintile, i.e. extremely bad news. We measure earnings surprise as $FE_{i,q} = (E_{i,q} - F_{i,q})/P_{i,q}$, where $E_{i,q}$ is the actual earnings per share announced in quarter q for firm i, $F_{i,q}$ is the median of the most recent forecasts from all individual analysts covering the stock, and $P_{i,q}$ is the stock price of firm i five trading days before the announcement in quarter q. Column1 reports the full sample test. Subsample tests are performed from Column 2 and 3 for top- and bottom-"*LSLI-Index*" terciles. Definitions of all other variables are listed in Appendix A. Both industry and time dummies are included, but coefficient estimates are omitted for brevity. Numbers in parentheses are *t*-statistics calculated using robust standard errors adjusted by heteroskedasticity and clustered at the firm level. ***, **, * indicate a two-tailed test significance level at the 1%, 5% and 10%, respectively.

	Earnings Surprise Quintile (FE_QRank)		
	Full Sample	T3(Highest)	T1(Lowest)
	(1)	(2)	(3)
Lottery	-0.051*	-0.065*	-0.025
	(-1.78)	(-1.85)	(-0.72)
Log(Size)	0.127***	0.133***	0.174**
	(4.00)	(3.48)	(2.28)
Log(BM)	-0.157***	-0.010	-0.024
	(-4.52)	(-0.72)	(-0.45)
Turnover	-0.082	-0.089*	-0.248**
	(-1.23)	(-1.74)	(-2.10)
Leverage	-0.431***	0.611***	-1.136***
	(-10.11)	(4.36)	(-6.99)
Constant	0.041	0.062	0.451**
	(0.90)	(0.36)	(2.41)
Observations	44,257	14,307	14,450
Pseudo R-squared	0.071	0.164	0.098
Industry Dummies	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes

Table 11: Non-ToM stock returns

This table examines the relation between types of stocks and non-ToM stock returns. Non-ToM trading days are defined as trading days that are not ToM trading days. The dependent variable is non-ToM stock returns. FE5 is a good news indicator variable that takes value of 1 if the earnings surprise ranks in the highest forecast error quintile and zero otherwise. FE1 is a bad news indicator variable that takes value of 1 if the earnings surprise ranks in the lowest forecast error quintile and zero otherwise. We measure earnings surprise as $FE_{i,q} = (E_{i,q} - F_{i,q})/P_{i,q}$, where $E_{i,q}$ is the actual earnings per share announced in quarter q for firm i, $F_{i,q}$ is the median of the most recent forecasts from all individual analysts covering the stock, and $P_{i,q}$ is the stock price of firm i five trading days before the announcement in quarter q. Column 1-3 reports the full sample test. Subsample tests are performed from Column 4 and 5 for top- and bottom-"*LSLI-Index*" terciles. Definitions of all other variables are listed in Appendix A. Both industry and time dummies are included, but coefficient estimates are omitted for brevity. Numbers in parentheses are *t*-statistics calculated using robust standard errors adjusted by heteroskedasticity and clustered at the firm level. ***, **, * indicate a two-tailed test significance level at the 1%, 5% and 10%, respectively.

Dependent Variable	Non-TOM Ret (%)				
	Full	Full	Full	T3 (Highest)	T1 (Lowest)
	(1)	(2)	(3)	(4)	(5)
Lottery	-0.018***	-0.017***	-0.015***	-0.022***	-0.010***
	(-10.01)	(-9.82)	(-6.43)	(-8.55)	(-6.02)
LSLI		-0.055			
		(-0.45)			
Lottery*LSLI		-0.019*			
		(-1.88)			
FE1			-0.114***	-0.107***	-0.088***
			(-3.41)	(-4.55)	(-2.82)
Lottery*FE1			-0.009*	-0.008*	-0.005
			(-1.78)	(-1.70)	(-0.89)
FE5			0.025***	0.033***	0.019**
			(5.67)	(3.74)	(2.00)
Lottery*FE5			0.004	0.007*	-0.001
			(1.44)	(1.90)	(0.78)
Log(Size)	-0.077***	-0.075***	-0.075***	-0.025***	-0.089***
	(-3.63)	(-3.82)	(-3.82)	(-5.33)	(-4.55)
Log(BM)	-0.155***	-0.234***	-0.200***	-0.187***	-0.222***
	(-6.03)	(-10.10)	(-3.10)	(-3.70)	(-2.99)
Turnover	0.078***	0.069***	0.023*	0.064***	0.055**
	(5.56)	(8.24)	(1.72)	(3.02)	(2.14)
Leverage	0.028*	0.010	0.025*	0.047**	0.029*
	(1.88)	(0.99)	(1.80)	(2.32)	(1.92)
Observations	12,457,434	12,457,434	12,457,434	4,570,574	4,094,258
Adj. R-squared	0.023	0.024	0.033	0.020	0.018
Time Dummies	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes

Table 12: ToM trading strategy and PEAD trading strategy

This table presents the regression results of daily returns of our arbitrage portfolio on several risk factors. In Panel A, the equally-weighted arbitrage portfolio consists of two parts: the portfolio of lottery-type stocks in areas of highest tercile of *LSLI-Index* and the portfolio of nonlottery-type stocks in areas of lowest tercile of *LSLI-Index*. The arbitrage portfolio will be long lottery-type stocks portfolio and short nonlottery-type portfolio in the 4 days of the ToM; and short the lottery-type portfolio and long the non-lottery portfolio in the non-ToM period of each month. The same strategy is repeated in Column (2) and (3) except that we exclude any stocks that have earnings news during ToM in Column (2) and that we exclude any stocks that have any earnings news in Column (3). In Panel B, the second trading strategy is to long all lottery-type stocks with good news (FE5) and short all lottery-type stocks with bad news (FE1) on each trading days of each ToM period, then hold the portfolio for 20 days. The same strategy is repeated in Column (2) and (3) except that we only include the portfolio of lottery-type stocks in areas of highest tercile of *LSLI-Index* Column (2) and that we only include the portfolio of lottery-type stocks in areas of lowest tercile of *LSLI-Index* in Column (3). MKT (Market Risk), SMB (Small Minus Big) , HML (High Minus Low), MOM (Momentum) are risk factors in the four-factor model.***, **, * indicate a two-tailed test significance level at the 1%, 5% and 10%, respectively.

Panel A: ToM Trading Strategy

	Portfolio Returns (%)		
		W/O EAs at ToM	W/O any EAs
VARIABLES	(1)	(2)	(3)
Market	0.367**	0.587***	0.898***
	(2.25)	(4.80)	(3.29)
SMB	0.300***	0.458***	0.724***
	(8.24)	(7.66)	(9.23)
HML	0.554***	0.982***	0.235***
	(10.04)	(10.00)	(8.82)
MOM	0.097**	0.117**	0.144**
	(1.98)	(2.29)	(2.01)
Constant (α)	0.068**	0.071***	0.062*
	(2.21)	(2.87)	(1.78)
Observations	7,905	7,905	7,905
Adj. R-squared	0.401	0.433	0.427

Panel B: PEAD Trading Strategy

	Portfolio Returns (%)		
	Full Sample	T3(Highest)	T1(Lowest)
VARIABLES	(1)	(2)	(3)
Market	0.026*	0.029*	0.036**
	(1.87)	(1.72)	(2.27)
SMB	0.014**	0.027**	0.018
	(2.14)	(2.04)	(1.33)
HML	-0.088	-0.079	-0.140**
	(-0.68)	(-0.78)	(-2.11)
MOM	0.041**	0.045*	-0.055
	(2.49)	(1.84)	(-1.27)
Constant (α)	0.055*	0.059**	0.024
	(1.68)	(2.04)	(0.67)
Observations	7,905	7,905	7,905
Adj. R-squared	0.205	0.277	0.252