Monthly Cyclicality in Retail Investors' Liquidity and Lottery-type Stocks at the Turn of the Month.

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Abstract

The well-documented underperformance of lottery stocks masks a within-month cyclical pattern. Demand for lottery stocks increases at the turn of the month, especially in areas whose demographic profile resembles that of the typical lottery-ticket buyers (i.e., gamblers), thus driving their prices higher. This effect is rooted in local retail investors' preference for lottery stocks and propelled by the within-month cyclicality of local investors' personal liquidity positions. A long-short investment strategy based on this cyclical pattern of lottery stocks performance yields gross abnormal returns of about 15% per year.

Keywords: Lottery-type stocks; turn-of-the-month effect; gambling; JEL codes: G14

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1. Introduction

We aim at providing evidence that will enable better understanding of speculative retail investors' role in the pricing of a category of stocks with lottery-like features (i.e., low price and high idiosyncratic volatility and skewness) that is known to attract their attention (Han and Kumar, 2013). Our investigation is focused on the performance of these stocks around the turn-of-the-month (hereafter, ToM) and its interplay with changes in personal liquidity affecting individuals' economic activity. The ToM provides a natural laboratory setting for addressing the importance of unsophisticated retail investors in the market of lottery stocks, and whether their presence is an indicator of predictable patterns in lottery stock performance.

Very much like state lotteries' tickets, stocks with lottery-like features attract investors who have strong propensity to gamble and tend to be poorer, less educated, urban, catholic, and belong to minority groups (Kumar, 2009a). 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 many economic activities follow a similar within-month cyclical pattern, with the largest swing in consumption having been observed for lottery sales (Evans and Moore, 2012). Thus, the investable capital of the typical gambling-motivated investor who likes lottery stocks is also expected to reach a trough just prior to the end of a calendar month and a peak shortly

thereafter, i.e. in the first few trading days of the new calendar month. If our conjecture is correct, the period of the peak in demand for lottery-type stocks by gambling-minded individual investors would coincide with the well documented ToM anomaly wherein stocks tend to perform better on trading days encompassing the change of a calendar month. Therefore, we hypothesize that the short-term surge in stock returns at the ToM would be stronger for lottery-type stocks than for non-lottery-type stocks and more pronounced among local 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 findings can be summarized as follows. We first document a strong positive relation between lottery-type stocks and ToM stock returns. Lottery-type stocks significantly outperform other stocks by about 3 basis points per day on average after controlling for time- and industry- fixed effects, the turn-of-week effect, and firm characteristics. We then show that the effect is particularly pronounced among lottery stocks in areas with an abundance of local investors that fit the lottery stock investor demographic profile, consistent with the notion that the exaggerated ToM performance of lottery stocks is driven by investors' desire to gamble.

We empirically confirm the link between superior ToM performance of lottery stocks and 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 in twosteps: first, we provide 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. Second, inspired by Evans and Moore (2012), we use the county-level change in mortality rate as a proxy for the change in local investors' personal liquidity position and document it is a driver of lottery-type stocks' ToM effect. This is particularly true in areas with greater concentration of local investors with high propensity to gamble on lottery-type stocks.

We account for several potential criticisms associated with endogeneity and causality, respectively. We address the possibility that there could be some unobservable characteristic correlated with being "lottery-type" that is affecting our results. In order to avoid problems from endogeneity, we use stock splits and headquarters' changes (i.e. exogenous shocks to the status and location of firms) to devise tests that are free of identification issues. Since stock price is one of the criteria for classifying stocks as lottery-type, the ToM effect should become 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". Additionally, we introduce an exogenous shock to firms' exposure to gamble-minded investors and examine companies that change headquarters to determine whether their ToM performance after relocating is affected by the demographic characteristics of the new location. Indeed, we document that the ToM effect becomes stronger (weaker) for lottery stocks that moved their headquarters in (out of) an area with many lottery-type stock investors. To provide a causal link between 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.

In the last part of our analysis, we address the issue of whether our results can be used by practitioners as the basis for an investment strategy. We show that a value-weighted arbitrage portfolio formed to exploit the within-month cyclicality in lottery stocks' performance outperforms by about 0.057% per day or about 14% per year.[1] Moreover, a second strategy designed to lower the potentially criticaleffect of transactions costs on the strategy's net returns yields gross alphas of about 15% per year.

Our paper follows past research showing that retail investors like to gamble and show preference for skewness (e.g., Shefrin and Statman, 2000; Kumar, 2009a; Barberis and Huang, 2008; Dorn and Huberman, 2010), or seek sensation through trading (e.g., Grinblatt and Kehloharju, 2009; Dorn and Sengmueller, 2009) and contributes to the literature that addresses the importance of retail investors in the pricing of stocks (e.g. see Han and Kumar (2013)). Specifically, we provide evidence that gambling-inclined investors' demand during the ToM, a period when personal liquidity constraints of such retail investors are relaxed, drives a surge of lottery-type stock prices.

Our evidence also complements recent research that suggests that lottery preferences can lead to destabilized stock prices (e.g., see Blau, Bowles, and Whitby

[1] Since this strategy is focused on relatively small firms and requires extensive rebalancing it is quite likely that gross returns could be largely extinguished by transactions costs (see Novy-Marx and Velikov (2014)). However, as stated in Novy-Marx and Velikov (2014) net returns can be improved by adjusting trading strategy toward a smaller number of relatively larger firms.

(2013) or Kumar, Page, and Spalt (2015)).We show that the demand for lottery stocks displays a monthly cyclical pattern driven by cyclicality in personal liquidity positions of gambling-minded investors. Moreover, we also show that it is the collective characteristics of lottery-type stocks (i.e. not just skewness, but also high volatility and low price all together) that matter in terms of producing the patterns shown in our results. Thus, our results are also in line with recent evidence that considering investor preference for lottery stocks can provide explanations for anomalies, such as "betting against beta" (see Bali, Brown, Murray and Tang (2013)), or for abnormal investment performance (see Frazzini, Kabiller, and Pedersen (2013)). We extend this part of the literature by illustrating a cyclical pattern in the manifestation of lottery preferences due to liquidity constraints. This result has potentially significant implications for corporate decisions related to the optimal timing of disclosure and financing. For example, it is possible that savvy corporate managers that are aware of these patterns would time announcements of bad earnings news or announcements of secondary equity issues so as they would occur during ToM days.

2. Background and hypotheses' development

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 (2009a) 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, 2009a), 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. Thus, our hypotheses can be summarized as follows:

<u>Hypothesis 1:</u> *The turn-of-month effect is more pronounced for lottery-type stocks than for all other 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 individual 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 retail investors' 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-type stocks' propensity to display a strong turn-of-month effect is driven by a change in the personal liquidity position of retail investors who are typically attracted to lottery-type investments.*

3. Data and Descriptive Statistics

3.1 Lottery Stocks

Our initial sample includes all stocks in the CRSP universe from 1980 to 2010. We follow Kumar (2009a) 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 in the lowest 50th stock price percentile, the highest 50th idiosyncratic volatility percentile, and the highest 50th idiosyncratic skewness percentile as lottery-type stocks. Stocks that 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.

Stock returns, trading volume, shares outstanding, and share price information are from the Center for Research in Securities Prices (CRSP). Idiosyncratic volatility and idiosyncratic skewness are measured following past papers (Kumar (2009a), Harvey and Siddique (2000), and Ang et al. (2006)) and computed at the end of month *t*, based on information from a 6-month window prior to month *t* (month *t*-6 to *t*-1).

3.2 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 control for several firm characteristics in our regression analysis. Detailed definitions of all variables and data sources can be found in the Appendix A. 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 *Friday* in our regression, which

equals one if the trading day is on a Friday and zero otherwise. Past 12-month returns is used in regression as a control for momentum. Common risk factors, such as Fama and French (1993) factors (*MKT, SMB, HML*) and the *UMD* factor from Carhart (1997), are also included in the return regressions. Our analysis accounts for several county-level variables that characterize local investors' demographic profile as well. 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 (2009a), 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 headquarters' locations, obtained from Compustat, as a proxy for firm locations. We use data from Prof. Bill McDonald's website (*http://www3.nd.edu/~mcdonald/10K_Headers/ 10-K_Headers.html*) to account for the fact that some firms changed headquarter locations over the sample period. The data are available from 1994-2010. 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:

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

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

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). 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 17,337,825 firm-trading day observations and 4,880,471 firm-ToM trading day observations over the period 1980-2010.

3.3 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 (2009a), 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, 2009a) in the long run. Consistent with Kumar (2009a), 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]

4. Empirical Results

4.1 ToM effect and lottery type stocks' performance in our sample

We begin our empirical investigation by examining whether our sample displays the general ToM effect and the under-performance of lottery-type stocks documented in previous studies. Our aim is to first confirm the overall return premium on lottery stocks

and the overall turn-of-the-month effect, and then to assess the magnitude of the differential turn-of-the-month effect for lottery stocks versus all other stocks in the market. We estimate the following model:

$$Ret_{i,t} = \beta_0 + \beta_1 Lottery_{i,t} + \beta_2 ToM_{,t} + \beta_3 Lottery_{i,t} * ToM_{,t} + \beta_4 Friday_t + \beta_5 \text{Log(Size)}_{i,t} +$$

$$\beta_6 \text{Log(BM)}_{i,t} + \beta_7 Turnover_{i,t} + \beta_8 Leverage_{i,t} + \beta_9 Past\_Ret_{i,t} + \beta_{10} \text{MKT}_{i,t} +$$

$$\beta_{11} SMB_{i,t} + \beta_{12} HML_{i,t} + \beta_{13} UMD_{i,t} + \sum time\ dummies + \sum Industries\ dummies$$

$$+ \varepsilon_{i,t} \qquad (2)$$

where $Ret_{i,t}$ is stock return measured at 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; $ToM_{i,t}$ is an indicator variable that equals one if the trading day t falls in the ToM period and zero otherwise. A host of control variables are firm size, book-to-market ratio, stock liquidity (measured by volume turnover as in Loughran and Schultz (2005)), leverage, past 12-month returns, common risk factors, and an indicator variable that takes the value of one if day t falls on a Friday. We also include time (year and month) as well as industry (defined at the 2-digit SIC-code level) indicator variables. $\varepsilon_{i,t}$ 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- and day level for all the regressions in this paper.

The ordinary least-squares (OLS) regression results are shown in Table 2. Columns 1 and 2 show the results of a model without controls and fixed effects. The *Lottery* coefficient is negative and significant, and the *ToM* coefficient is positive and

significant. Thus, these results, together with the univariate evidence from Table 1, confirm that the ToM effect and the underperformance of lottery-type stocks in our sample are of roughly the same magnitude as in prior studies. Moreover, the coefficient estimate of the interaction term, *Lottery * ToM* 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 interaction coefficient estimate is 0.033, indicating that lottery-type stocks on average have 0.033% higher daily returns during the turn of the month period. Columns 3 present results estimating the full model shown in Eq. (5). The *Lottery*, *ToM* and *Lottery * ToM* coefficients retain their sign, magnitude and significance even after controlling for firm characteristics, industry- and time-fixed effects.

In the last three columns of Table 2 we examine whether lottery stocks' ToM effect is driven by any of the three characteristics (low stock rice, high idiosyncratic skewness and high idiosyncratic volatility) that together classify a stock as lottery-type. The results show that no individual lottery-stock characteristic has, by itself, a significant impact on the ToM effect. Thus, taken together, the findings in Table 2 support the notion that there is the lottery stocks' ToM effect, and it is not driven by a single lottery-stock characteristic. In the next section we will take a closer look at the mechanism of this positive relationship between lottery stocks and ToM effect.

[Please insert Table 2 here]

4.2 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 (2009a), 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 3 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* and *ToM*. 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 (2009a). 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 estimate the model using an index (*LSLI-Index*) that comprises all six proxies for the concentration of local lottery-type stocks investors. For the sake of brevity, we denote each of the above seven variables as a *DemoFactor* and estimate the following regression model:

$$Ret_{i,t} = \beta_0 + \beta_1 Lottery_{i,t} + \beta_2 ToM_{,t} + \beta_3 Lottery_{i,t} * ToM_{,t} + + \beta_4 DemoFactor_{i,t} + \beta_5 DemoFactor * Lottery_{i,t} + \beta_6 DemoFactor * ToM_{i,t} + \beta_7 DemoFactor * ToM * Lottery_{i,t} + \sum Controls + \varepsilon_{i,t} \quad (3)$$

The main variable of interest in this regression model is thus *DemoFactor * ToM * Lottery*, which gives us some idea about whether the more pronounced ToM effect for lottery-type stocks is driven by its lottery-like feature itself or the demographic characteristics associated with their investors. Collectively, the 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, the negative and significant coefficient estimate of *InstOwn* indicates that low institutional ownership is associated with better stock performance at the ToM. More importantly, the interaction term *DemoFactor * ToM * Lottery* also has a negative and significant coefficient, 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, lower annual household income, 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.

Interestingly, 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 * ToM* coefficient becomes insignificant in all but one model, 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.[2] Finally, it should be noted that since the typical investor who exhibits lottery preferences largely shares the characteristics of someone with binding monthly liquidity constraints, our demographic measures in Table 3 could be capturing a combination of lottery preferences and monthly liquidity constraints. We address the importance of personal liquidity constraints in a later section.

[2] Although the interactions effects shown in Table 3 could be emanating from variation in local investors' lottery preferences they could also be driven by variation in local investors' personal liquidity constraints. We address this issue in a later section. Also, based on the evidence of Kumar, Page and Spalt (2013) and Korniotis, Kumar and Page (2013) we would expect that the ToM effects we reveal would be more pronounced when local bias is stronger. In unreported tests, we confirm this hypothesis. Results of these additional tests are suppressed for the sake of brevity but are available from the authors upon request.

[Please insert Table 3 here]

4.4 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.

4.4.1 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 it constitutes an exogenous decrease in stock price, which renders the stock more lottery-like since a low stock price is one of the criteria for being a lottery type-stock. This test can indicate whether the ToM effect is driven by demand for lottery-type stocks and not some unobservable characteristic correlated with being 'lottery-type'.

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.(2), 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:

$$Ret_{i,t} = \beta_0 + \beta_1 Split_{i,t} + \beta_2 ToM_{i,t} + \beta_3 Split * ToM_{i,t} + \sum Controls + \varepsilon_{i,t} \quad (4)$$

The first three columns of Table 4 report the regression results estimating Eq. (4), 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 * ToM* 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, we sort our sample into terciles based on the *LSLI-Index*. Firms that are located in the highest (lowest) *LSLI-Index* tercile group are considered to be exposed to many (few) local investors with strong preference for lottery-type stocks. The coefficient of *Split * ToM* is positive and significant in the highest *LSLI-Index* tercile group (*High-LSLI* area, hereafter) but it becomes insignificant in the lowest *LSLI-Index* tercile group (*Low-LSLI* area, hereafter). 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 next three columns of Table 4 report the regression results estimating Eq. (4), 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 * ToM* 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.

Finally we address the possibility that stock splits may be associated with other differences in the stock, or may simply be attention-grabbing events that attract retail investors for reasons that may have little to do with lottery preferences. Thus, in the last three columns of Table 4 we performed the stock split tests for the subsample of firms that are not lottery stocks either before or after the split. The results in columns (7)-(9) show that the split dummy's coefficient is not significant in any regression. Thus, our main results are not driven by these aforementioned possible effects.

[Please insert Table 4 here]

4.4.2 Other identification tests

We also investigate the impact of local trading on lottery stocks' ToM effect by accounting for exogenous shocks that can either directly constrain local trading or

effectively reduce the stocks' recognition by local investors favoring stocks with lottery characteristics.

In the first test we follow Shive (2012) and examine whether the ToM effect of lottery-type stocks becomes weaker when local trading is constrained by a power outage. [3] 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. In the second test, we consider headquarter relocations as exogenous shocks to firm's exposure to gambling-minded investors. We investigate whether the corresponding change in concentration of local lottery stock investors can impact the ToM effect of lottery-type stocks. If the previously documented ToM effect of lottery-type stocks is driven by local gamblers' demand, we expect lottery type firms would experience a stronger (weaker) ToM effect when they move from a *Low(High)-LSLILSLI* area to a *High(Low)-LSLILSLI* area due to a corresponding change in demand during ToM.[4]

[3] 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. 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.

[4] The address change data are from McDonald's website (http://www3.nd.edu/ ~mcdonald/10-K_Headers/10-K_Headers.html). It reports header information on the 10-K report from SEC's EDGAR website, including the occurrence of headquarter change of filing firms from 1996-2010.

The results of these tests are shown in Appendix B and provide additional strong support for the notion that the ToM effect of lottery-type stocks is at least partly driven by demand of local investors who have a preference for such stocks.

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

Since the liquidity position of people with limited income and wealth typically deteriorates towards the end of month and recovers at the beginning of the next month (Evans and Moore, 2012), 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. Indeed the demographic characteristics that predict lottery participation are also characteristics that would be associated with more binding monthly liquidity cycles. That is, households with lower income and education are more likely participate in lotteries, but also are more likely to live paycheck-to-paycheck. Thus, it is hard to identify whether the interaction effects we found in Table 3 are coming from variation in lottery preferences versus variation in personal liquidity constraints. In the next two sub-sections, we provide identification tests designed to establish a direct link

between the cyclicality of lottery stock investors' personal liquidity positions and lottery-type stocks' performance at the ToM.

4.5.1 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 (2009a) 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:

$$EBSI_t = \beta_0 + \beta_1 ToM + \beta_2 UNEMP_m + \beta_3\, UEI_m + \beta_4\, MP_m + \beta_5\, RP_m + \beta_6\, TS_m + \varepsilon_{i,t} \qquad (5)$$

The dependent variable is the excess buy-sell imbalance (EBSI) on day *t* of a given month. It is defined as *EBSIt =LotBSIt −RemBSIt*, where *LotBSIt*, is the day *t* buy–sell imbalance of a portfolio of lottery stocks, and *RemBSIt* is the day *t* buy–sell imbalance of a portfolio that contains the 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 5 presents the time series regression estimating Eq. (4). The results show that although 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.

To more directly address the conjecture that the lottery stock investor demographic profile index (*LSLI-Index*) can be proxying for both lottery preferences and personal liquidity constraints, we re-estimate the model for subsamples formed based on state-level per capita lottery expenditures as a proxy for investor preferences toward lottery-type stocks employed by Kumar (2009a). Column 5 and 6 show the results of the test performed using the subsamples of firms located in states ranking in the top and bottom terciles on lottery-type stock preferences, respectively. The coefficient of the ToM dummy is only significant at 10% level for the high preference tercile, indicating that indeed both lottery preferences and liquidity constraints need to be present to generate the observed TOM effect.

[Please insert Table 5 here]

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

Our last identification strategy involves devising a measure of personal liquidity changes by taking some other phenomenon that has been tied to monthly household

liquidity and use it to identify cross-sectional variation in the degree to which the personal liquidity constraints' monthly cycle is binding. 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 use the county-level change in mortality at the turn of month to identify change in personal liquidity of local investors, and argue that if the spike in mortality around the turn of the month is bigger for a given county, we may infer that the monthly pay cycles are more binding for households in that county, and in turn the lottery stock ToM effect should be more pronounced in counties with large changes in mortality around the ToM.

In Table 6 we regress *ΔMortality* and its interaction with *Lottery* and *ToM*, using the model specification shown in Eq.(3) and replacing the demographic factor variable with *ΔMortality*. 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, 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 1989-2010 periods. Indeed, we obtain similar results across the two sub-period tests. The coefficient of the main variable of interest, *ΔMortality* Lottery*ToM*, 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*ToM* 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 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.

While this analysis produces intuitive results, we acknowledge that there are two potential problems associated with it. One is the possibility that changes in mortality rates at the turn of the month may be capturing something else other than the degree to which gambling-inclined investors' monthly pay cycles become binding. The other concern is with respect to the approximation measure for the mortality rate used in the post-1988 period due to the incomplete information on daily death rates. This latter concern is less serious in light of the consistent results obtained from the two subsamples.

[Please insert Table 6 here]

4.6 Trading Strategies

In this subsection, we investigate whether a trading strategy designed around the patterns found in 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. In unreported tests we also found that the underperformance of local lottery-type stocks during non-ToM periods is exacerbated when there is high concentration of this type of investor in the area. Thus, in our first trading strategy, we consider an arbitrage portfolio formed by taking opposite (long/short) positions during the ToM and non-ToM days of each month in two extreme portfolios: the portfolio of lottery-type stocks and the portfolio of nonlottery-type stocks. 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. The second trading strategy involves only lottery-type stocks from *High-LSLI* area that are both larger and more likely to display price pressure effects around the ToM.

We then estimate the risk-adjusted performance of the two strategies' portfolios using the four-factor model (Fama and French, 1993; Carhart, 1997) and daily returns and present the results in Table 7. Columns 1-3 (4-6) show results using equally-weighted (value-weighted) returns for the first strategy, and columns 7 and 8 show equally-weighted and value-weighted returns for the second strategy's portfolio .

Column 1 in Table 7 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 0.053, indicating that our arbitrage portfolio's risk-adjusted daily return is 5.3 basis points, which corresponds to about 13.4% 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. We also repeat the test by examining the performance of the investment strategy when the stocks involved are only from the areas with high and low concentration of lottery-stock local investors. Columns 2 and 3 report the coefficient estimates of the four-factor regression model for the subsample portfolios in areas with many (*High-LSLI* area) and few (*Low-LSLI* area) gamblers, respectively. The alpha estimate is positive and significant at the 1%-level with a magnitude of 0.060 in Column 2, while it is not significant in Column 3. The results indicate that while the trading strategy is even more profitable (annual alpha of about 15.1%) when applied to the portfolios that only include firms located in the high concentration of lottery-stock local investors, it fails to outperform the regression-based benchmark when applied using the portfolios that only include firms located in areas with few investors that fit the profile of a lottery-type stock investor. To alleviate the concerns that equally-weighted portfolio strategies could have a) upward-biased returns (see Asparouhova et al., 2013), and b) much greater associated transactions costs (Novy-Marx and Velikov, 2014) we also report results based on this trading strategy using the value-weighted portfolio in Column 4-6 of Table 7. The gross return of the value-weighted arbitrage portfolio is somewhat reduced relative to that of the equally-weighted arbitrage portfolio. Moreover, the net return from this strategy that requires extensive monthly

rebalancing and is based on less liquid (small, lottery-type) investments would likely be practically wiped out by transactions costs. According to Novy-Marx and Velikov (2014) "Transaction costs consequently generally reduce realized spreads by more than 1% of the monthly one-sided turnover, i.e., if the long side of a strategy turns over 20% per month, the realized long/short spread will be at least 20 bps per month lower than the gross spread, and the statistical significance of the spread will be reduced proportionately." Thus, transactions costs for strategies of this type (small firm-based with sizeable rebalancing every month) can run well above 1% per month. With the second strategy, we explore whether a variant strategy designed to reduce monthly turnover and transaction costs can also deliver similar gross alphas, which would imply net returns have improved. Thus, here we hold a portfolio that consists only of lottery-type stocks from *High-LSLI* areas that fulfill the following criteria: a) rank in the top half in terms of number of ToM positive returns over the past year, i.e. be more likely to display price pressure effects around the ToM, and b) be relatively large (rank above the median in terms of firm size). The gross alpha from this second strategy is similar to those in first strategy which implies that the lottery stocks' ToM effect can potentially be economically meaningful.

[Please insert Table 7 here]

5. Conclusion

In contrast to 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, common risk factors 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 attributed to being a lottery-type stock *per se*. For example, ToM returns of lottery-type stocks are significantly stronger after stock splits or after headquarters moves to areas with high concentration of gambling-minded local investors. More importantly, we show that the ToM effect for lottery-type stocks is at least partially driven by the within-month cycle of such investors' 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.

Our paper makes several contributions to the literature. First, we provide valuable insight into the within-month cyclical behavior of lottery-type stocks and deliver 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 contribute to the literature that addresses the importance of retail investors in the pricing of stocks and highlight the importance of demographics in empirically gauging retail investor behavior. Third we add new evidence that it is not the individual characteristics of lottery-typestocks (i.e., high skewness, high volatility, or low price) but their combination that matters in producing the positive ToM return pattern. Finally, our evidence provides the basis for the blueprint of investment strategies that can be used by practitioners.

Most importantly, our findings have several implications for future research. For example, the existence of a sizeable gambler-investor base that arguably is more prone to inattention may be associated with greater under-reaction to relevant news. For example, if local retail investors who like lottery-type stocks tend to pay less attention to news

during periods they can gamble more, then earnings announcements issued at the ToM should be associated with more post-earnings announcement drift. Moreover, if the cyclical, within-month pattern of lottery stock prices is persistent, managers may be tempted to manage the timing of news, with more bad earnings news announced at ToM days and more good news at non-ToM days. In conjunction, the above two scenarios could be contributing to the lottery stocks' ToM effect, but also to the overall monthly cyclicality of lottery stock prices our paper has documented.

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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 Performance	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 Main Regressions		
Ret (%)	Stock returns on all trading days in percentage	CRSP
Ret_ToM (%)	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
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
Past Returns	Past 12-months returns	CRSP
Friday	An indicator variable equals one if the trading day falls on a Friday and zero otherwise	
Low_Prc	An indicator variable if the stock in the lowest 50th stock price percentile and zero otherwise	CRSP
High_Skew	An indicator variable if the stock is in the highest 50th idiosyncratic volatility percentile and zero otherwise	CRSP
High_Idio	An indicator variable if the stock is in the highest 50th idiosyncratic skewness percentile and zero otherwise	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 daily 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 a variable.	U.S. Census, CDC, 13F, ARDA
EBSI	Excess buy-sell imbalance	Brokerage

HQIn	An indicator variable that equals one if a firm moves from a *Low-LSLI* area to a *High-LSLI* area and zero otherwise	Compustat
HQOut	An indicator variable that equals one if a firm moves from a *High-LSLI* area to a *Low-LSLI* area and zero otherwise	Compustat
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

Appendix B: Identification Tests – Power outage and headquarter changes

This table examines the effect of power outage and headquarter change on stock returns. Column 1-3 show the results for power outage test. 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 regression model follows the specification of Column 3 in Table 2, with the addition of *Outage* indicator as well as its interactions with *Lottery* and *ToM*. *Outage* equals one if the firm is located in the blackout area, and zero otherwise. Column 4-9 show the results for headquarter change test. The regression model follows the specification of Column 3 in Table 2, except that we replace the main variable of interest with two indicators of headquarter change, *HQIn* and *HQOut*, in Column 4-6 and 7-9 respectively. *HQIn* equals one if a firm moves from a Low-LSLI area to a High-LSLI area, and zero otherwise. *HQOut* equals one if a firm moves from a High-LSLI area to a Low-LSLI area and zero otherwise. These two indicator variables are lagged 1-2 years in Column 5-6 and Column 8-9, respectively. Definitions of all variables are listed in Appendix A. In all specifications, coefficient estimates of control variables are omitted for brevity. Both industry and time dummies are included, but coefficient estimates are suppressed for brevity as well. Numbers in parentheses are t-statistics calculated using robust standard errors adjusted by heteroskedasticity and clustered at the firm and the day level. ***, **, * indicate a two-tailed test significance level at the 1%, 5% and 10%, respectively.

Dependent Variable	Daily stock returns %								
	Full Sample	T3 (Highest)	T1 (Lowest)	Lag = 0	Lag = 1	Lag = 2	Lag = 0	Lag = 1	Lag = 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ToM	0.016**	0.015**	0.019***	0.016**	0.015**	0.019***	0.015**	0.014**	0.013**
	(2.02)	(2.32)	(2.85)	(2.02)	(2.32)	(2.85)	(2.03)	(2.35)	(2.15)
Lottery	-0.021**	-0.025***	-0.018**	-0.019**	-0.021**	-0.017**	-0.014**	-0.013*	-0.019**
	(-2.28)	(-2.69)	(-2.00)	(-2.26)	(-1.99)	(-2.10)	(-2.22)	(-1.90)	(-2.22)
Lottery*ToM	0.017**	0.022**	0.010*	0.031***	0.022**	0.010*	0.022**	0.015*	0.011*
	(2.07)	(2.36)	(1.77)	(3.10)	(2.36)	(1.77)	(2.13)	(1.90)	(1.72)
Outage	-0.009*	-0.007	-0.006						
	(-1.78)	(-1.14)	(-1.36)						
Lottery*Outage	0.003	-0.005	0.001						
	(0.88)	(-0.14)	(0.36)						
ToM*Outage	0.002	-0.002	0.001						
	(0.28)	(-1.00)	(0.25)						
Lottery*ToM*Outage	-0.0014**	-0.016***	-0.007						
	(-2.28)	(-2.94)	(-0.76)						
HQIn				0.003	0.002	0.002			
				(0.42)	(0.33)	(0.20)			
Lottery*HQIn				0.002	-0.004	0.004			
				(0.85)	(-1.11)	(1.08)			
HQIN*ToM				0.004	0.003	0.006			
				(1.07)	(1.11)	(1.23)			
Lottery*ToM*HQIn				-0.002	0.004	0.018**			
				(-0.79)	(1.45)	(2.09)			
HQOut									
Lottery*HQOut							-0.003	-0.002	-0.003
							(0.80)	(-1.09)	(1.09)
HQOUT*ToM							0.001	-0.005	0.002
							(0.67)	(-1.18)	(0.77)
Lottery*ToM*HQOut							-0.002	-0.007*	-0.020***
							(-0.86)	(-1.76)	(-2.83)
Observations	17,337,825	17,337,825	17,337,825	17,337,825	17,337,825	17,337,825	17,337,825	17,337,825	17,337,825
Adj. R-squared	0.0212	0.0205	0.0208	0.0142	0.0143	0.0185	0.0161	0.0150	0.0222
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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
Ret (%)	3,852,649	0.053	9.105	-3.859	0	4.656	13,485,176	0.071	6.352	-2.539	0	3.896	-0.018	-25.26***
ToM_Ret (%)	1,069,876	0.302	7.689	-2.564	0	2.465	3,810,595	0.21	3.631	-1.075	0	1.339	0.092	18.86***
Size (mils)	3,852,649	99.8	340.3	17.1	43.8	114.2	13,485,176	1570	5982.4	110.8	385.2	1409	-1470.2	-20.66***
BM	3,852,649	0.689	0.675	0.218	0.482	0.888	13,485,176	0.401	0.472	0.213	0.423	0.687	0.288	29.35***
Turnover (%)	3,852,649	0.651	3.585	0.053	0.198	0.567	13,485,176	0.923	23.534	0.093	0.277	0.736	-0.272	-13.43***
Leverage	3,852,649	0.469	0.658	0.241	0.419	0.626	13,485,176	0.542	0.208	0.368	0.519	0.638	-0.073	-10.53***
Past returns (%)	3,852,649	10.58	67.58	2.68	8.95	13.65	13,485,176	19.67	48.36	6.58	13.36	23.69	-9.09	
InstOwn	3,852,649	0.213	0.203	0.056	0.15	0.314	13,485,176	0.516	0.217	0.452	0.630	0.762	-0.303	-19.62***
Urban	3,852,649	0.476	0.5	0	0	1	13,485,176	0.433	0.495	0	0	1	0.043	12.06***
CathoDum	3,852,649	0.475	0.485	0	0	1	13,485,176	0.382	0.485	0	0	1	0.093	18.22***
Catho/Prot	3,852,649	2.524	2.039	0.776	2.012	3.854	13,485,176	2.402	1.917	0.635	1.7	3.736	0.122	15.06***
Income (000s)	3,852,649	40.15	11.66	42.36	45.33	55.86	13,485,176	50.16	11.51	42.67	49.932	63.32	-10.01	-9.88***
AfriWhi	3,852,649	0.252	0.281	0.057	0.14	0.294	13,485,176	0.197	0.222	0.045	0.113	0.254	0.055	26.55***
Education	3,852,649	34.43	9.448	24.876	28.545	39.12	13,485,176	36.287	9.153	26.98	31.232	40.05	-1.861	-23.84***
ΔMortality %	3,852,649	0.005	0.024	0.0142	0.004	0.006	13,485,176	0.0033	0.0171	0.0029	0.0029	0.003	0.0017	19.43***

Table 2 Lottery-type stocks, ToM effect and stock returns

This table examines the differential ToM effect for lottery-type stocks versus other stocks. The dependent variable is the daily stock returns. The independent variables are lottery-type stock dummy, ToM dummy, and other control variables, such as firm size, book-to-market ratio, turnover volume, Friday indicator variable, past 12-months returns, and four risk factors in the four-factor model. Definitions of all variables are listed in Appendix A. In column 2-6, 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. In Column 4-6, the main independent variables are low price dummy (*Low_Prc*), high skewness dummy (*High_Skew*), high idiosyncratic volatility dummy (*High_IdioVol*), respectively. Numbers in parentheses are t-statistics calculated using robust standard errors adjusted by heteroscedasticity and clustered at the firm and the day level. ***, **, * indicate a two-tailed test significance level at the 1%, 5% and 10%, respectively.

Dependent Variable	Daily stock returns (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
ToM	0.019**	0.018**	0.014*	0.020**	0.019**	0.020***
	(2.13)	(2.20)	(1.89)	(2.22)	(2.13)	(2.73)
Lottery	-0.021**	-0.012**	-0.010**			
	(-2.38)	(-2.08)	(-2.15)			
Lottery*ToM		0.035***	0.025**			
		(3.16)	(2.43)			
Low_prc				0.009		
				(0.88)		
Low_prc*ToM				0.013		
				(1.22)		
High_skew					0.013	
					(1.27)	
High_skew*ToM					-0.006	
					(-0.57)	
High_idio						0.004
						(0.52)
High_idio*ToM						0.004
						(0.76)
Log(Size)			-0.042***	-0.026***	-0.029***	-0.028**
			(-4.47)	(-3.23)	(-3.46)	(-2.41)
Log(BM)			-0.054**	-0.012*	-0.043**	-0.055***
			(-2.23)	(-1.69)	(-2.33)	(-2.68)
Turnover			0.285**	0.115	0.198*	0.225*
			(2.40)	(1.13)	(1.76)	(1.70)
Leverage			0.087**	0.043	0.038	0.062*
			(1.99)	(1.30)	(0.76)	(1.79)
Friday			0.223***	0.203***	0.253***	0.237***
			(7.10)	(7.00)	(8.76)	(7.56)
Past returns			0.020**	0.015*	0.018**	0.019*
			(2.15)	(1.78)	(1.85)	(1.69)
MKT			0.464***	0.473***	0.408***	0.363***
			(5.70)	(5.45)	(6.02)	(5.81)
SMB			-0.222**	-0.237*	-0.258**	-0.245*
			(-2.18)	(-1.90)	(-2.06)	(-1.92)
HML			-0.078*	-0.063	0.048	-0.055

			(1.87)	(1.23)	(1.08)	(1.37)
UMD			0.018	0.025*	0.007	0.013
			(1.45)	(1.70)	(1.23)	(0.69)
Constant	0.053***	0.042***	0.168***	0.135***	0.127***	0.013**
	(13.33)	(5.65)	(6.45)	(5.22)	(5.01)	(2.00)
Observations	17,337,825	17,337,825	17,337,825	17,337,825	17,337,825	17,337,825
Adj. R-squared	0.0099	0.0105	0.0325	0.0328	0.0327	0.0330
Time Dummies	No	Yes	Yes	Yes	Yes	Yes
Industry Dummies	No	Yes	Yes	Yes	Yes	Yes

Table 3 ToM stock returns and local lottery-type investors

This table examines the relation between types of stocks and daily stock returns during ToM and non-ToM period, introducing interaction terms with seven 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. In each column, one of the seven demographic variables is used in the regression under the name, *DemoFactor*. Definitions of all variables are listed in Appendix A. The base specification replicates Column 3 in Table 2, with the addition of each *DemoFactor* as well as its interactions with *Lottery* and *ToM.* In all specifications, the set of control variables include firm size, book-to-market ratio, turnover volume, Friday indicator variable, past 12-months returns, and four risk factors in the four-factor model, but coefficient estimates are omitted for brevity. Both industry and time dummies are included, but coefficient estimates are suppressed for brevity as well. Numbers in parentheses are t-statistics calculated using robust standard errors adjusted by heteroscedasticity and clustered at the firm and the day level. ***, **, * indicate a two-tailed test significance level at the 1%, 5% and 10%, respectively.

Dependent Variable	Daily stock returns (%)						
	InstOwn	Urban	Catho/Prot	AfriWhi	Log(Income)	Education	LSLI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ToM	0.011**	0.012*	0.008*	0.012**	0.010**	0.010**	0.009*
	(2.32)	(1.72)	(1.90)	(1.99)	(2.06)	(2.14)	(1.69)
Lottery	-0.014	-0.022*	-0.005	-0.016**	-0.012*	-0.015*	-0.010
	(-1.52)	(-1.69)	(-0.65)	(-2.00)	(-1.77)	(-1.89)	(-1.65)
Lottery*ToM	0.010	-0.002	0.011	0.013*	0.016	0.015	0.003
	(1.32)	(-0.49)	(0.49)	(1.78)	(0.85)	(1.13)	(0.45)
DemoFactor	0.083**	0.006	0.008	0.015	-0.007	-0.012	0.012
	(2.33)	(1.25)	(0.61)	(1.12)	(-0.52)	(-1.13)	(0.71)
Lottery*DemoFactor	0.011	-0.023**	-0.005	-0.163	0.001	-0.015	-0.006
	(1.00)	(-2.08)	(-0.53)	(-1.38)	(1.10)	(-0.92)	(-0.70)
ToM*DemoFactor	-0.003	0.002	0.009	0.038	-0.014	-0.002	0.010
	(-0.30)	(0.22)	(0.86)	(1.20)	(-0.53)	(-0.75)	(1.23)
Lottery*DemoFactor *ToM	-0.117***	0.017*	0.015**	0.034**	-0.055**	-0.036***	0.213***
	(-3.18)	(1.70)	(2.08)	(1.98)	(-2.27)	(-2.90)	(3.82)
Observations	17,337,825	17,337,825	17,337,825	17,337,825	17,337,825	17,337,825	17,337,825
Adj. R-squared	0.0212	0.0205	0.0208	0.0220	0.0023	0.0221	0.0203
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 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 that were lottery-type prior to the stock split, and remained lottery type after the stock split. In Group 3, we perform the test for firms that are nonlottery-type either before or after splits. The sample only includes 12 months prior to and after the stock split event. The regression model follows the specification of Eq.(5), 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, turnover volume, Friday indicator variable, past 12-months returns, and four risk factors in the four-factor model, but coefficient estimates are omitted for brevity. Industry, stock and time dummies are included, but coefficient estimates are suppressed for brevity. Numbers in parentheses are t-statistics calculated using robust standard errors adjusted by heteroscedasticity and clustered at the firm and the day level. ***, **, * indicate a two-tailed test significance level at the 1%, 5% and 10%, respectively.

Dependent Variable	Daily stock returns (%)								
	Group 1 (IV, skewness)			Group 2 (Lottery stocks before and after splits)			Group 3 (Nonlottery stocks either before or after splits)		
	Full Sample	T3 (Highest)	T1 (Lowest)	Full Sample	T3 (Highest)	T1 (Lowest)	Full Sample	T3 (Highest)	T1 (Lowest)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ToM	0.005	0.012**	0.014**	0.014**	0.011**	0.011**	0.009*	0.012*	0.004
	(0.87)	(2.05)	(2.13)	(2.27)	(2.07)	(2.18)	(1.90)	(1.80)	(1.20)
Split	0.003	-0.010	-0.002	-0.003	0.001	0.004	0.002	0.001	0.005
	(1.09)	(-1.17)	(-0.37)	(-0.79)	(0.48)	(1.28)	(0.37)	(0.46)	(0.88)
Split*ToM	0.009*	0.011**	0.004	0.007**	0.0008**	0.006**	0.003	0.000	0.006
	(2.03)	(2.22)	(1.13)	(2.36)	(2.28)	(1.99)	(0.87)	(0.25)	(1.35)
Observations	3,612,107	1,230,365	1,240,252	2,144,067	698,068	702,246	5,326,879	1,425,983	1,436,250
Adj. R-squared	0.0184	0.0176	0.0185	0.0167	0.0153	0.0165	0.0112	0.0103	0.0164
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5 ToM stock returns and change in local lottery-type investors' personal liquidity positions

This table 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. Column 1 and 2 show the results of the full sample tests. Column 3 and 4 show the results of subsample tests based on *LSLI-Index* terciles. Column 5 and 6 show the results of subsample tests based on terciles of lottery-type stocks preference. We use the state-level per capita lottery expenditures as a proxy for each stock. Definitions of all variables are listed in Appendix A. ***, **, * indicate a two-tailed test significance level at the 1%, 5% and 10%, respectively.

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	T3 (Highest)	T1 (Lowest)	Highest Pref. Tercile	Lowest Pref. Tercile
	(1)	(2)	(3)	(4)	(5)	(6)
TOM dummy	0.154*	0.102	0.089**	0.075	0.167*	0.053
	(1.74)	(1.28)	(2.10)	(0.95)	(1.86)	(1.04)
Lagged UNEMP		0.199**	0.217***	0.194**	0.233**	0.145*
		(2.33)	(2.85)	(2.11)	(2.31)	(1.78)
Lagged UEI		-0.056	0.543*	0.182	0.152	0.211*
		(-1.23)	(1.74)	(0.56)	(0.98)	(1.69)
Lagged MP		-0.020	-0.043	-0.182*	-0.078	-0.043
		(-0.77)	(-1.21)	(-1.73)	(-0.85)	(-1.33)
Lagger RP		0.488***	0.272**	0.133*	0.528**	0.363**
		(5.62)	(1.98)	(1.90)	(2.30)	(2.18)
Lagged TS		-0.256	-0.278*	-0.047	-0.127	-0.147
		(-1.44)	(-1.87)	(-0.82)	(-1.33)	(-1.05)
Constant	0.138	0.085	-0.043	0.532	0.166**	0.098
	(0.87)	(1.52)	(-0.32)	(1.03)	(2.31)	(1.28)
Number of Days	1,499	1,499	1,499	1,499	1,499	1,499
Adj. R-squared	0.014	0.070	0.095	0.085	0.030	0.031

Table 6 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 3. Correspondingly, tests using the 1980-1988 sample for which *ΔMortality* can be measured accurately are performed in Columns 4 to 6. 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 regression model follows the specification of Column 3 in Table 2, with the addition of *ΔMortality* indicator as well as its interactions with *Lottery* and *ToM*. Definitions of all variables are listed in Appendix A. In all specifications, coefficient estimates of control variables are omitted for brevity. Both industry and time dummies are included, but coefficient estimates are suppressed for brevity as well. Numbers in parentheses are t-statistics calculated using robust standard errors adjusted by heteroscedasticity and clustered at the firm and the day level. ***, **, * indicate a two-tailed test significance level at the 1%, 5% and 10%, respectively.

Dependent Variable	Daily stock returns %					
	1989-2010			1980-1988		
	Full Sample	T3 (Highest)	T1 (Lowest)	Full Sample	T3 (Highest)	T1 (Lowest)
	(1)	(2)	(3)	(4)	(5)	(6)
ToM	0.016***	0.014**	0.020***	0.026***	0.020**	0.028***
	(3.32)	(2.17)	(2.85)	(3.78)	(2.25)	(4.85)
Lottery	-0.018**	-0.024***	-0.012*	-0.014**	-0.016*	-0.016*
	(-2.08)	(-2.90)	(-1.89)	(-1.98)	(-1.70)	(-1.77)
Lottery*ToM	0.005	0.003	0.007	-0.029	0.010*	0.004
	(1.28)	(1.02)	(0.80)	(-0.37)	(1.82)	(0.42)
ΔMortality	0.057	-0.006	0.187	0.086	0.062	0.096
	(0.28)	(-0.04)	(1.00)	(0.37)	(0.40)	(0.48)
ToM*ΔMortality	-0.059	0.198	0.051	-0.714	0.149	0.411*
	(-0.32)	(1.00)	(1.02)	(-0.99)	(1.33)	(1.87)
Lottery*ToM*ΔMortality	3.285**	3.354**	-0.545	3.801**	4.636***	0.879
	(2.03)	(2.38)	(-0.86)	(2.33)	(4.55)	(1.13)
Observations	12,307,173	4,102,322	4,102,368	5,030,652	1,676,795	1,676,758
Adj. R-squared	0.015	0.013	0.007	0.018	0.019	0.011
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Table 7 Trading Strategies

This table presents the regression results of daily returns of our arbitrage portfolio on several risk factors. The first arbitrage portfolio is equally-weighted and consists of two parts: the portfolio of lottery-type stocks and the portfolio of nonlottery-type stocks. We then assess the performance of the following trading strategy: long the lottery-type stocks portfolio and short the nonlottery-type portfolio during ToM days, then reverse the position and go short the lottery stocks portfolio and long the non-lottery stocks portfolio during the non-ToM days of each month. The full sample result and the subsample results for firms located in the *High-LSLI* area and in the *Low-LSLI* area are shown in Column 1-3, respectively. The second arbitrage portfolio is same as the first, except that all stocks in the portfolio are value-weighted. Corresponding regression coefficients are reported in Column 4-6. Column 7 and 8 present the results for the second trading strategy that utilizes a subsample of lottery stocks. At the end of month and beginning of ToM, we go Long lottery stocks with the following characteristics: in the High-LSLI area, rank above 50% in terms of number of ToM positive returns over the past year, and rank above 50% in terms of the firm size. At the beginning of any month and the end of the ToM period, we sell stocks if their price exceeds the purchase price. *MKT* (Market Risk), *SMB* (Small Minus Big) , *HML* (High Minus Low), *UMD* (Up Minus Down) are risk factors in the four-factor model.***, **, * indicate a two-tailed test significance level at the 1%, 5% and 10%, respectively.

Dependent variable	Portfolio Returns (%)							
	Strategy 1: EW			Strategy 1: VW			Strategy 2:	
	Full Sample	T3(Highest)	T1(Lowest)	Full Sample	T3(Highest)	T1(Lowest)	EW	VW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MKT	0.038***	0.030**	0.029**	0.026*	0.023**	0.036**	0.018	0.03**
	(2.69)	(2.23)	(2.50)	(1.87)	(2.02)	(2.27)	(1.23)	(1.89)
SMB	0.023***	0.019***	0.012*	0.014**	0.034*	0.032	0.033**	0.018
	(3.36)	(3.10)	(1.75)	(2.14)	(1.85)	(1.23)	(2.04)	(1.02)
HML	-0.118**	-0.106*	-0.063	-0.088	-0.072	-0.142**	0.007	0.033
	(-2.23)	(-1.82)	(-1.07)	(-0.68)	(-0.85)	(-2.15)	(0.86)	(1.06)
UMD	0.022*	0.018	0.016	0.041**	0.052*	-0.051	-0.047*	0.057**
	(1.90)	(0.68)	(1.05)	(2.49)	(1.82)	(-1.32)	(-1.73)	(2.33)
Constant (α)	0.053**	0.060***	0.013	0.050*	0.057**	0.021	0.061***	0.059***
	(1.99)	(2.84)	(0.45)	(1.68)	(2.03)	(0.82)	(2.99)	(2.76)
Adj. R-squared	0.157	0.162	0.133	0.155	0.177	0.152	0.088	0.080