Do Behavioral Needs Influence the Trading Activity of Individual Investors? Evidence from Repeated Natural Experiments[*]

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Abstract

Multiple natural experiments of large jackpot lotteries in Taiwan are used to document a substitution effect between individual investor trading and lottery buying. We establish five key findings. First, when the jackpot exceeds 500 million Taiwan dollars (about 15 million U.S. dollars), the number of shares traded by individual investors decreases by about 7% among stocks with high individual trading fraction, low market capitalization, high past returns, and high past turnover. Second, our approach reveals that the substitution effect is stronger among stocks with lottery features, with a decline in trading of about 9% among stocks with high return volatility and skewness. Third, the magnitude of the documented substitution effect increases monotonically with the jackpot. Fourth, firm-level trading activity reacts negatively to lottery drawings, and is statistically significant for a sizable number of firms. Finally, the aggregate number of shares traded by individual investors declines by 6% with lottery offerings. We attribute the substitution effect exemplified here to behavioral trading needs of individual investors, such as entertainment, sensation seeking, and gambling, and it appears consistent with the wider predictions of behavioral economics and finance.

JEL Classification: G10, G12, G13, C51.

Keywords: Natural experiments; lottery; stock trading; substitution effect; investor attention; behavioral trading needs.

1. Introduction

Recent research documents behavioral reasons why individual investors trade. However, few studies quantify how behavioral trading motives can systematically affect trading activities in the stock market.

Our contribution is to take advantage of multiple natural experiments of large jackpot lotteries in Taiwan to address five questions: Does the presence of large lotteries reduce shares traded for stocks which manifest greater behavioral biases on the part of individual investors? Does trading activity of stocks with lottery features decline on large lottery jackpot days? How strong is the substitution effect between lottery and shares traded, as the jackpot increases? Do lotteries impact firm-level trading activities? And finally, is the effect also discernible at the aggregate market level? Our empirical investigation blends the role of investor attention, behavioral biases, and preference for certain types of stocks, which enables us to isolate possible motives for trading among individual investors.

Several features motivate us to study the lottery and stock market behavior in Taiwan. First, a large jackpot lottery can be regarded as a natural experiment because it is a pure outcome of probability, and it is independent of the stock market. Second, the Public Welfare lottery has been popular since its inception in 2002, while other forms of gambling are prohibited. Third, on average, about 70% of the trading value in the Taiwan stock market (TSE) originates from individual investors, as opposed to other major stock markets where institutional investors typically dominate. With high individual investor participation in the stock market and no other legal gambling venues, Taiwan offers a tractable setting to empirically investigate the relation between lottery buying, jackpot size, attention, behavioral biases, and trading activity in the stock market.

Lottery can be relevant to individual investor trading for a number of reasons. First, lottery has combined attributes of entertainment, sensation generation , and gambling (e.g., Thaler and Ziemba (1988), Brenner and Brenner (1990), and Statman (2002)). Second, lottery's payoff is positively skewed, a feature preferred by investors under the cumulative prospect theory (e.g., Tversky and Kahneman (1992) and Barberis and Huang (2008)). Finally, when the jackpot is large, it attracts media coverage and investor attention, and, hence, individual investor trading could be affected both

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for certain types of stocks, and at the level of the aggregate stock market.

Based on hand-collected lottery data from January 2002 to December 2009, we contribute to the research on individual investor trading from two angles. For one, we offer market-wide empirical evidence on why individual investors trade, which is as important as the evidence using individual investor data.[1] For another, our natural experiments help to minimize concerns of endogeneity, while revealing the interlinkages between individual investors' trading behavior and lottery buying.

Our empirical specifications establish core findings. Importantly, we present evidence that the effect of lottery on trading activity is pronounced among stocks that are favored by individual investors (see Gompers and Metrick (2001), Dorn and Huberman (2010), and Kumar (2009a)): stocks associated with high individual trading fraction, low market capitalization, high past returns, and high past turnover experience a reduction in shares traded by about 7% on days with a jackpot in excess of 500 million TWD (about 15 million U.S. dollars), whereas the effect is statistically insignificant for stocks sharing the opposite property.

An even stronger substitution effect is observed for stocks with lottery features. Particularly, the shares traded of stocks with high return volatility and skewness are seen dropping by about 9% on large lottery days. In light of the behavioral biases of individual investors, trading in more speculative stocks is accordingly more severely affected when the jackpot is large, which appears consistent with the arguments of Barber and Odean (2008), Barberis and Huang (2008), and Kumar (2009b).

Whereas buying lottery with a large jackpot can be a substitute for stock trading by individual investors, a larger prize amplifies the thrill of lottery participation, which leads to a potentially testable implication using our lottery jackpot data. The crucial insight is that the size of the jackpot matters, and the magnitude of the substitution effect increases monotonically in the lottery jackpot.

With respect to firm-level effects, our results offer complementary supportive evidence: the number of shares traded by individual investors drops, on average, by 7.6% if there is a large jackpot

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[1]Among the multitude of reasons, Dorn and Sengmueller (2009) show, for example, that investors who report enjoying investing or gambling rebalance their portfolios more frequently, and Grinblatt and Keloharju (2009) find that investors who are more prone to sensation seeking tend to trade more frequently. Besides, the studies of Kumar (2009a, 2009b) imply that the propensity to gamble correlates with investment decisions.

lottery drawing on the same day. The negative impact on trading activity is statistically relevant for a sizable number of firms.

We also substantiate a substitution effect between lottery buying and trading by individual investors in the aggregate. For instance, when the lottery jackpot size exceeds 500 million Taiwan dollars, the number of shares traded by individual investors decreases by 6%. The negative impact of lottery on individual trading is both economically and statistically significant.

Our paper is most related to Barber, Lee, Liu, and Odean (2009), who analyze whether market turnover rate changed after the introduction of the Public Welfare lottery in Taiwan. They find that lottery introduction reduced turnover rate by about one-fourth. They argue that a contributing factor may be that investors view trading in the stock market as an opportunity to gamble or as a sensation-seeking activity. However, our paper differs from theirs in two key ways, and yet complements their study. First, instead of studying a one-time event, we use our lottery data to explore a series of drawings with large jackpots over eight years. The repeated event setting enables us to analyze more directly the link between lottery buying and stock trading. The novelty of a series of natural experiments on trading by individual investors is what also distinguishes our paper from Dorn (2009). Second, the time-series setting allows a comprehensive documentation of the substitution effect both among groups of stocks with different characteristics, and also at the individual firm level.

The rest of the paper proceeds as follows. Section 2 provides a discussion of the literature most closely related to our work. Section 3 describes the lottery and stock market data underlying our natural experiment, while Section 4 presents our empirical results. Conclusions and summary of our findings are provided in Section 5.

2. Connection to the literature on investor attention, behavioral needs, and preference for stocks with lottery features

This section provides a review of the related literature, and aims to put our empirical findings in the wider context of behavioral finance and economics.

2.1. Investor attention

Investor attention on particular stocks can be affected through several channels, but the following two are most related to our paper. First, Tetlock (2007), Tetlock, Saar-Tsechansky, and Macskassy (2008), Barber and Odean (2008), and Fang and Peress (2009) document that media coverage and content can affect stock trading and prices in crucial ways. Second, Gervais, Kaniel, and Mingelgrin (2001), Kaniel, Ozoguz, and Starks (2010), Barber and Odean (2008), and Seasholes and Wu (2007) show that investor attention can be captured through abnormal past volume, return, and price patterns. Following a different approach, Da, Engelberg, and Gao (2010) show that Google search frequency can be used to proxy retail investor attention.

The literature mentioned above, however, focuses on investor attention captured by one or few stocks among all listed ones. At the same time, it has been documented that investor attention might be captured by other events outside the stock market, which also have an impact on investor trading behavior. For example, Edmans, García, and Norli (2007) argue that investor mood is affected by international soccer outcomes through all forms of media. They find a significant stock market decline after soccer losses. Kaplanski and Levy (2010) examine the effect of aviation disasters on stock prices and find evidence of a significant negative event effect. They also attribute the result to the negative sentiment driven by a bad mood and anxiety, which affects investment decisions and, hence, asset valuations.

Our paper can be viewed as building on the investor attention literature, since lottery drawings with large jackpots usually attract media coverage. Rather than changing the mood of investors, a large jackpot satisfies investor needs and caters to their preference that are similar to stock trading. Therefore, a lottery with a large jackpot can affect investor trading activities in certain segments of the stock market.

2.2. Behavioral needs and preference for stocks with lottery features

Grinblatt and Keloharju (2001) find evidence that individual trading is affected by past returns and historical price patterns, such as being at a monthly high or low. Grinblatt and Keloharju (2009)

show that overconfident investors, and those investors more prone to sensation seeking, trade more frequently. Likewise, Dorn and Sengmueller (2009) show that investors who report enjoying investing or gambling rebalance their portfolio at twice the rate of their peers in a survey study. Overall, the entertainment value of trading in the stock market constitutes an additional attribute that is capable of rationalizing the "excessive trading puzzle," but the effect is yet to be fully understood.

Important to us, Barberis and Huang (2008) show that the cumulative prospect theory framework can capture the common preference for lottery-like, or positively skewed, wealth distributions. This implication can explain why some investors take a large undiversified position in securities with right-skewed payoffs. In particular, Kumar (2009b) shows that individual investors prefer stocks with lottery features, i.e., those capturing high stock return volatility and high stock return skewness. Institutional investors, on the contrary, stay away from those stocks. Statman (2002) advances the analogy between lottery players and stock traders from perspectives of overoptimism, aspiration, emotion, and entertainment, while Thaler and Ziemba (1988) rationalize the purchase of a lottery ticket as paying for a fantasy, given lottery's negative expected return.

Large jackpot lotteries usually receive media coverage, inducing individual investors to pay more attention to the lottery drawing. Participating in such a lottery can be a substitute for stock trading because it satisfies investors' craving for entertainment, sensation-seeking, and gambling. Therefore, the substitution effect between lottery and stocks could be a result of a combination of investor attention towards lottery and their behavioral trading needs for certain types of stocks. We use the context of repeated natural experiments to study the relation between lottery and individual trading activity.

3. Data description of the natural experiments

Before proceeding to details of our data, we emphasize that we study repeated natural experiments in which the presence of a large lottery serves as an instrument for days when individual investors' need for thrill-seeking behavior is manifested by buying lottery. The idea is that the thrill of the lottery jackpot, perhaps intensified by the media coverage around the event, substitutes the need

for other forms of thrill-seeking activities, for instance, trading by individual investors in the stock market, a channel that can be more explicitly identified within our natural experiment setting.

3.1. Public welfare lottery and large jackpots

The Public Welfare Lottery, also known as Lotto, was introduced on January 22, 2002 to fund social welfare programs. A $50 TWD (32 TWD is roughly 1 U.S. dollar) ticket allows buyers to choose 6 numbers out of 42, so the first prize winning probability is one in 5.2 million. Lotto drawings are held twice a week.

Big Lotto was introduced in 2004, in which buyers can choose 6 numbers out of 49, so the first prize winning probability is one in 14 million. Big Lotto drawings are also held twice a week when Lotto is not drawn. With a lower probability of hitting the jackpot, the cumulated prize of Big Lotto is, in general, larger than Lotto. In 2007, Lotto was replaced by Super Lotto, with the odds of hitting the Super Lotto jackpot being one in 22 million. Since our interest lies primarily in the link between large jackpots and stock trading by individual investors, we do not distinguish among Lotto, Big Lotto, or Super Lotto in our empirical inquiry.

The media usually reports the cumulated prize of a lottery drawing as its jackpot, so we use the two terms interchangeably. Table 1 shows descriptive statistics of the lottery jackpot size between 2002 to 2009. In total, we have 1,495 lottery drawings (see column 2), ranging from 99 drawings in 2002 to 248 in 2006. The data is hand collected from the website of the bank which holds the exclusive rights to administer the lottery.

Inspection of Table 1 also shows that the calender year mean of the jackpot ranges from 147 million TWD to 470 million TWD, over 2002 to 2009. The maximum winnable jackpot prize was 2.93 billion TWD.

For the vast majority of our analysis, a large jackpot is taken to be a cumulated lottery prize above 500 million TWD, which roughly represents the 90th percentile value of the sample. Hence, we also report, in Table 1, the number of lottery drawings with a jackpot larger than 500 million TWD. There is some variation in the number of large jackpot drawings over our eight year sample,

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ranging between 11 and 37 drawings. In total, there are 163 large jackpot lotteries above 500 million TWD.

Large jackpots, such as those above 500 million, only occur after a series of no winners, and they are governed by pure probability outcomes and are statistically independent of return movements in the stock market. Therefore, we regard these 163 large lottery jackpots as a series of natural experiments, and subsequently use them as instruments of thrill-seeking activity.

3.2. Stock market and trading activity

Data on our natural experiment also includes matching daily stock market data from TSE. Excluding firms with less than 100 trading day observations leaves 734 individual stocks in our sample, and includes individual investor trading activity in each stock. Table 2 reports the median of daily trading activity variables across all years, and in each calendar year from 2002 to 2009.

The first data trait worth emphasizing is that stock market trading is dominated by individual investors: the ratio of shares traded by individual investors over total shares traded ranges between 52% to 76% (compare columns 2 and 3). Such a high individual investor participation rate indicates that behavioral biases, if any, could exert an identifiable impact on the stock market.

In our analysis, the daily market turnover is the number of shares traded divided by the sum total of the number of shares outstanding on the TSE, the same as the equal weighted aggregate market turnover in Baker and Wurgler (2007). The median daily market turnover is around 0.61%, somewhat larger than the value-weighted aggregate turnover of 0.45% for S&P 500 index stocks (see Chordia, Roll, and Subrahmanyam (2010, Table 1)). Individual turnover is analogously the number of shares traded by individual investors divided by the total shares outstanding in the market. The median daily individual turnover is around 0.39%.

Lottery sales over the value of shares traded, as seen from the last column of Table 2, decreases gradually from 0.97% to 0.10% from the lottery debut to the last three years in our sample. The relative value of lottery sales, even though small, can still impact trading activity through behavioral channels, and is at the center of our study.

4. How does lottery influence trading activity?

This section addresses our main research questions related to lottery jackpots: Does the presence of large lotteries reduce shares traded for stocks which manifest greater behavioral biases on the part of individual investors? Does trading activity of stocks with lottery features decline on large lottery jackpot days? How strong is the substitution effect between lottery and shares traded, as the jackpot increases? Do lotteries impact firm-level trading activities, and is the effect also discernible at the aggregate market level? We provide evidence on these questions in turn. Our results are important as they shed light on possible behavioral motives for trading by individual investors and the impact of such motives on certain segments of the market.

4.1. Lottery reduces trading activity of stocks preferred by individual investors

Stemming from the fact that large jackpots often attract media coverage and, therefore, investor attention, we initially focus on lottery drawings with jackpots larger than 500 million TWD (around 15 million U.S. dollars), the 90th percentile of the jackpot distribution. Via such a specification of jackpots, we have a series of natural experiments. We reiterate that natural experiments are our central object of interest, since (i) a large jackpot is a pure outcome of probability, and (ii) the outcome is independent of the stock market. It is the setting of repeated natural experiments on individual trading that differentiates our lottery study from the existing empirical literature.

First, we consider proxies for a set of stocks which are favored by individual investors, instead of institutional investors (e.g., Statman (2002), Coval and Shumway (2005), Dorn and Huberman (2010), and Kumar (2009a)). The underlying hypothesis is that the substitution effect between lottery jackpot and stock trading is likely to be concentrated among stocks where behavioral biases are most pronounced. Our motivation is to show that when behavioral biases do sway the action of individual investors, the size of the lottery jackpot can have a differential impact on the trading of certain types of stocks.

To build on the above theme, we construct four yardsticks of how much a certain stock type is preferred, or more often traded by individual investors.

- *Individual trading fraction:* Number of shares traded by individual investors divided by the total number of shares traded. If a stock's average trading fraction between day $t-4$ to $t-25$ is top (bottom) 30th percentile, we classify this stock as a high (low) individual trading fraction stock on date t. Then, we sum up the number of shares traded across all stocks in each of the three groups, and label them as high (H), medium (M), and low (L). We repeat this approach each day in the sample, and construct the corresponding time series.

- *Market capitalization:* Share price of a stock multiplied by the number of shares outstanding. Stocks with high market capitalization on date t are those stocks which fall in the top 30th percentile of average capitalization between day $t-4$ to $t-25$. The low capitalization stocks are analogously defined.

- *Past returns:* Measured by the 22 day average return between day $t-4$ to $t-25$. Stocks with high (low) past returns on date t are those stocks whose average returns fall in the top (bottom) 30th percentile.

- *Past turnover:* Number of shares traded on day t divided by the shares outstanding in a stock. Stocks with high (low) turnover on date t are those stocks which appear in the top (bottom) 30th percentile of turnover between day $t-4$ to $t-25$.

Our proxies for stock types that are preferred by individual investors are in line with earlier studies, for example, Gompers and Metrick (2001), who observe that institutional investors are more disposed toward stocks that are larger and more liquid, and with relatively low past returns (see also Hirshleifer (2001) and Foucault, Sraer, and Thesmar (2010)). Falkenstein (1996) likewise shows that mutual funds prefer stocks with high visibility and low transaction costs.

Consider the following generic empirical specification:

$$\log(V_{p,t}) = \beta_0 + \beta_{p,1} D_t^{Jackpot} + \beta_{p,2} \log(\overline{V}_{p,[t-4 \to t-25]}) + \varepsilon_{p,t}, \qquad \text{for } p = H, M, L, \quad (1)$$

where $V_{p,t}$ is the number of shares traded for a stock portfolio sharing high, medium, and low characteristics (i.e., $p = H, M, L$) respectively. In equation (1), $\overline{V}_{p,[t-4 \to t-25]}$ is the average of lagged trading activities between day $t-4$ to $t-25$ pertaining to the stock characteristic. We add the lagged

terms $\overline{V}_{p,[t-4 \rightarrow t-25]}$ to control for possible persistence in trading activity. Also, since the same type of lottery is drawn twice a week, we skip the trading between day $t - 1$ to $t - 3$. ε_t is a zero-mean disturbance term.

At the heart of our approach is $D_t^{Jackpot}$, which represents a dummy variable for a large jackpot lottery and equals one when the cumulated prize is larger than 500 million TWD, and zero otherwise. One may view the large jackpot dummy as an instrument when (i) the investor's need for thrill-seeking behavior is satisfied by buying lottery, and (ii) the investor's thrill-seeking behavior is tilted towards certain stocks, for instance, those preferred by individual investors, and (iii) there is a substitution effect between lottery buying and share trading by individuals in those stocks. Through equation (1), we investigate whether shares traded on day t are affected by the large jackpot on the same day.

Histogram evidence (not reported for brevity) confirms that while the level of the shares traded are skewed to the right, the empirical distribution of the log counterpart is closer to normal. Moreover, visual inspection of the plots of log variables suggests the time series are also stationary. Still, to substantiate that our empirical specifications do not suffer from a near unit root problem, we have performed the Phillips and Perron (1988) unit root test on the number of shares traded. The null hypothesis of a unit root is rejected at 1% confidence level with a t-statistic of -6.80 (the critical value is -3.46).

Some core lessons can be learned based on the regression coefficients and the p-values reported in Table 3. Taking into consideration potential econometric concerns associated with the time-series properties of shares traded, we display the two-sided p-values for the coefficients based on the Newey and West (1987) heteroscedasticity and autocorrelation consistent (HAC) covariance matrix estimator. Our procedure relies on the Bartlett kernel and no prewhitening. Throughout, to gauge the statistical significance of the estimated coefficients in specification (1), we use an input of 7 for the lag length. This input is determined by the number of observations (i.e., 1,989) raised to the power $1/4$, as is often suggested, for instance, in Greene (2007).

When we classify stocks according to *high* individual trading fraction between day $t - 4$ to $t - 25$ (see Panel A of Table 3), its number of shares traded by individual investors declines by 7.2% on a

lottery drawing day with a large jackpot. Given the two-sided p-value of 0.030, one can reject the null hypothesis that the lottery has zero effect on the shares traded. In the other extreme, namely those stocks that are least sought after by individual investors, one can observe an attenuation in the negative lottery impact. With a p-value of 0.509, the effect is statistically indistinguishable from zero. In sum, stocks whose trading activity is dominated by individual investors experience a deterioration in shares traded when the lottery jackpot is large.

A similar overall picture is obtained when considering stocks classified by market capitalization (Panel B of Table 3). In particular, the coefficient on the large jackpot dummy is -7.8% and statistically significant (p-value is 0.032) for low capitalization stocks, while the effect is statistically insignificant (p-value is 0.145) for large capitalization stocks. Accordingly, our results support a more pronounced and statistically reliable effect of large lottery on trading activities connected with low capitalization stocks. These results appear compatible with the notion that behavioral attributes of individual investors can disproportionately impact low capitalization stocks.

For those stocks falling in the high past returns category, the reduction in trading activity is of the order of -11.5% (p-value is 0.004) and strongest among all our proxies. In contrast, for stocks with the lowest past returns category, the counterpart coefficient is positive but statistically indistinguishable from zero (Panel C of Table 3). Equally important, and uniformly consistent with the above findings, Panel D of Table 3 implies that stocks with high past turnover are more affected by lottery with a decline of 7.1%, compared with an insignificant 5.7% for stocks with low past turnover.[2]

Both results, namely, from high past returns and high past turnover, concur with the predictions of attention grabbing: if a stock has performed well, or has been actively traded in the past month, it spurs more individual trading due to greater investor attention. Therefore, such stock's trading declines more by the presence of a large jackpot lottery, as substantiated in Table 3.

Summarizing our findings from this part of the investigation, the effect of lottery is stronger among stocks with (i) high individual trading fraction, (ii) low market capitalization, (iii) high past

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[2]Reported in the final column are the p-values for the null hypothesis that the regression coefficients are jointly equal to zero. The joint p-values from the estimations are all below 0.050. The variable $\overline{V}_{p,[t-4\to t-25]}$ is positive and strongly significant. With the goodness-of-fit adjusted R^2 of the regressions close to 50%, the fit of the estimations is reasonable.

returns, and (iv) high past turnover. The documented substitution effect between lottery and shares traded is related to studies, including, for example, Loughran and Schultz (2004), who find that aggregate volume in locally headquartered stocks falls 17% in blizzard-struck cities. Shive (2010) uses large power outages as a natural experiment and finds that turnover in the median stock falls 23% during a local blackout.

In an approach resembling ours, Jacobs and Weber (2010) exploit regional holidays in Germany as a natural experiment in investor distraction; they show that holidays affect stock-level turnover, and they attribute their finding to local bias among investors. Instead, our channel is rooted in the combined effect of attention grabbing events and a preference for certain types of stocks by individual investors. We now proceed to strengthen our evidence from yet another perspective.

4.2. Trading in stocks with lottery features is adversely impacted by lottery jackpot

Relying on theories from behavioral economics and finance (e.g., Tversky and Kahneman (1992), Golec and Tamarkin (1998), and Barberis and Huang (2008)), we now investigate the link between investors' preference for stocks with lottery features, trading activity, and lottery jackpot. Specifically, we pose the following question: How strong is the substitution effect between lottery and shares traded of stocks with lottery features?

To answer this question, we construct two surrogates for stocks with lottery features, specifically stock return volatility and stock return skewness, as essentially suggested in the previous studies of French, Schwert, and Stambaugh (1987), Campbell, Lettau, Malkiel, and Xu (2001), Harvey and Siddique (2000), and Bakshi and Madan (2006). Here we are also guided by the feature that individual stocks, especially in emerging markets, often have high idiosyncratic return components and, hence, a close correspondence exists between total return volatility and skewness and their idiosyncratic counterparts (see, among others, Bakshi, Kapadia, and Madan (2003), Ang, Hodrick, Xing, and Zhang (2010), and Bekaert, Hodrick, and Zhang (2010)).

Continuing, we construct the return volatility of a stock each day as its past 22 day return

quadratic variation. Return skewness of a stock each day is computed based on the past six month's daily returns. The use of a longer history to compute skewness has been recommended by Kim and White (2004) and Bai and Ng (2005), and is consistent with the approach taken by Kumar (2009b).

We compute the return volatility (skewness) of all the stocks in our sample each day, and then bin available stocks into three groups, respectively representing high (top 30th percentile), medium, and low (bottom 30th percentile) volatility (skewness) stocks. For each group, we compute the sum total of shares traded and then build the time series of shares traded. Stocks with high dispersion and highly (positively) skewed returns are important to the studies of Boyer and Vorkink (2007), Boyer, Mitton, and Vorkink (2010), Kumar (2009b), Bali, Cakici, and Whitelaw (2010), and to the economic theory of Barberis and Huang (2008).

Performing regressions analogous to those in specification (1), we report the results in Table 4. The results are informative from theoretical and empirical perspectives. First, trading activity of stocks exhibiting high return volatility falls by 9.1% (the p-value is 0.001), whereas the effect of lottery for stocks with low volatility is statistically insignificant (the p-value is 0.519). At the same time, the tabulated results indicate that trading activity of stocks with high (i.e., positive) return skewness declines more on large jackpot days compared to stocks with low skewness.[3]

Overall, the negative lottery impact is consistent with the view that a large lottery diverts investor attention away from the stock market, especially that of individual investors. Buying lottery with a large jackpot also serves as a substitute for stock trading because it satisfies individual investors' craving for entertainment, sensation-seeking, and gambling. Our setting of repeated natural experiments captures the idea that lottery and stock trading are substitutes, and the presence of a large lottery offering can translate into lower trading activity for stocks more affected by behavioral biases and stocks with lottery features.

Combining the results from Tables 3 and 4, two other points are worthy of further emphasis. First, using a natural experiment to tackle the concern of reverse causality, or endogeneity, has been

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[3]Our inference has so far rested on the p-values for the lottery dummy in Table 3 and 4. If we adopt the dependent variable to be the log difference in shares traded of high and low grouping of a characteristic, while using the log difference of the average past trading activity of the high and low grouping as the control, the results are mostly in tandem with those reported. The p-values on the lottery dummy are smaller than 0.050 for individual trading fraction, past returns, and return volatility, thereby dispensing the need to report these results in parallel.

widely adopted in labor and development economics, and in finance. See, among others, Landry, Lange, List, Price, and Rupp (2009), Duflo, Kremer, and Robinson (2008), Bittlingmayer (2002), Fishe and Robe (2004), Chari and Henry (2005), Gan (2007), and Foucault, Sraer, and Thesmar (2010). Second, isolating the trading activities by individual investors, as opposed to total shares traded, can capture the impact of behavioral biases and, hence, reinforce our findings that hinge on the availability of repeated natural experiments.

4.3. The substitution effect is monotonic in size of the lottery jackpot

One concern is that the 500 million TWD cutoff of a large jackpot might be arbitrary. To accommodate this concern, we alter our specification in equation (1) to consider alternative threshold levels of lottery size of 400, 600, and 700 million TWD, which respectively represent the 85th, 92nd, and 95th percentile of the jackpot distribution. When the lottery jackpot increases, it translates into fewer jackpot day dummies but often attracts greater media coverage.

Rather than report all the coefficient estimates, we use Figure 1 to convey the most essential point of this exercise. The gist is that when the estimated coefficients on the jackpot dummy are plotted against the size of the jackpot, respectively for each stock type studied in Tables 3 and 4, it reveals a monotonically declining pattern.

[Figure 1 about here.]

Even though not tabulated, there are 17 p-values (out of 24 total) that are below 0.050, and there are 22 p-values below 0.100, testifying to the strength of the monotonicity of the substitution effect between lottery and shares traded. The effect is also asymmetric across stock types. In particular, for high past return stocks, the negative impact of lottery gets more pronounced, from -7.4% to -17%, as the jackpot increases from 400 million to 700 million TWD. A similar strong effect is validated for stocks with high return volatility and high return skewness.[4]

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[4]One may theorize that a larger jackpot elicits greater media attention, implying a lower cost to an investor to learn about the lottery in general. Such a lower cost, in turn, could reduce the need to allocate scarce resources in the form of investor attention, and perhaps produce a diminished effect on the trading behavior of a lottery. Our results in Figure 1 broadly counter such an argument across a range of lottery prizes.

The takeaway is that the substitution between lottery buying and trading by individual investors is more intimately linked as the jackpot increases. The documented monotonic pattern is not at odds with behavioral arguments, since a larger jackpot attracts more investor attention, and the lottery-stock substitution is prevalent only among some types of stocks.

Reconciling our evidence, we attribute these findings to the distraction caused by a large jackpot lottery. Since lottery could also satisfy behavioral needs of individual investors, our contention is that large jackpot lotteries serve as a substitute for trading in the stock market, and the effect is concentrated in certain investor habitats.

4.4. Lottery negatively impacts trading activity at the firm level

Our thrust here is to propose firm-level regressions with trading activities, which control for changes in the composition of firms that might otherwise confound tests that rely on aggregate trading activities. Some cross-sectional differences in lottery effects could get washed away under aggregation. An additional advantage of individual firm regression is that we can simultaneously control for the past trading activity of the firm as well as that of the market.

Specifically, the dependent variable in each firm-level regression is its trading activity by individual investors. That is, for each stock i, we perform the following time-series regression for its own trading activity $V_{i,t}$,

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\begin{aligned}
\log(V_{i,t}) \;=\; & \beta_{0,i} \;+\; \beta_{1,i} D_t^{Jackpot} \;+\; \beta_{2,i} \log(\overline{V}_{i,[t-4 \to t-25]}) \\
& + \; \beta_{3,i} \log(\overline{V}_{m,[t-4 \to t-25]}) \;+\; \varepsilon_{i,t}, \qquad \text{for } i = 1,\ldots,I.
\end{aligned} \tag{2}
$$

The explanatory variables are a large lottery dummy $D_t^{Jackpot}$ (see equation (1)), $\overline{V}_{i,[t-4 \to t-25]}$ is the average of lagged trading activities between day $t-4$ to $t-25$, and $\overline{V}_{m,[t-4 \to t-25]}$ represents the average of lagged market trading activity by individual investors between day $t-4$ to $t-25$. $\varepsilon_{i,t}$ denotes a zero-mean disturbance term. Our motivation for including both $\overline{V}_{m,[t-4 \to t-25]}$ and $\overline{V}_{i,[t-4 \to t-25]}$ is to control for the persistence of trading activity and potential unobserved firm heterogeneity.

To measure the impact of lottery on firm trading activity, we perform the estimation (2) for each

firm separately, keeping in mind the concerns of Petersen (2009) and Skoulakis (2009). Moreover, guided by frugality of presentation, we summarize our results from three perspectives, as also, for example, in Bakshi, Kapadia, and Madan (2003) and Fung and Hsieh (2001). First, we report the average sensitivity to assess the mean effect. Second, we report the t-statistic for the average sensitivity, under the assumption that sensitivity coefficients are i.i.d. across firms. Finally, we count the number of firms that share the same sign as the average sensitivity, and have p-values less than 0.050 or 0.100 according to the Newey and West (1987) HAC estimator. The number of $\beta_{1,i} < 0$ coefficients with significant p-value in equation (2) bears critically on our analysis.

At the outset, observe that Table 5 shows that the large lottery dummy has a negative impact on trading activity by individual investors. What is noteworthy is that the number of shares traded drops, on average, by 7.6% when there is a large jackpot lottery drawing on the same day (see the row marked Avg. for the Unrestricted model), mirroring our previous findings. The t-statistic on the average sensitivity is -19.03, as seen from the row marked "t-stat." The negative average impact of lottery maintains its significance even after we omit the control for the average of the lagged number of shares traded by individuals in the market.

Equally important, there are 107 firms (see the row marked #, p-val.< 0.05) that support a negative coefficient on $D_t^{Jackpot}$ in the unrestricted model in equation (2), and yet have a p-value less than 0.050 associated with $\beta_{1,i}$ according to the Newey and West (1987) HAC estimator. The number of firms rises to 172 when the significance criterion is relaxed to p-value less than 0.100.

A common conclusion to draw based on Tables 3, 4, and 5 is that both the effect for certain types of stocks and the average firm-level effect remain strongly significant. When the jackpot is large, the resulting media coverage attracts individual investor attention and accordingly affects individual investor trading. While one may be concerned that our results might be affected by some other exogenous events in the market, the concern is alleviated by two considerations. First, it is unlikely that those events are correlated with the lottery drawings with large jackpots. Second, the effect of lottery permeates to the trading activity of a sizable number of individual firms.

4.5. The effect of lottery jackpot is also affirmed in aggregate trading activity

Table 6 presents the market-level regression results when the dependent variable is the aggregate trading activities of individual investors. The crucial result to be garnered from Panel A of Table 6 is that large lottery exerts a negative impact on shares traded in the aggregate. Essentially, we find that the number of shares traded decreases strongly by 6.0% (the two-sided p-value is 0.050).

To put the above results in perspective, a 6.0% reduction in trading activity by individual investors corresponds to a 116.9 million reduction in share trading (given that the median of daily shares traded is 1.948 billion; see Table 2), thereby leading to a 2.5 billion TWD trading value impact (given the median per share price of 21 TWD; see Table 2). Thus, the magnitudes of the coefficients on $D_t^{Jackpot}$ are both economically and statistically significant.[5]

The question to ask now is: Do our results stay intact if one adopts alternative measures of aggregate trading activity? We address this question in two ways, where we first employ the log of the value traded as a proxy for trading activities (from TSE). The presence of a large jackpot lottery significantly reduces the amount of trading activity in the stock market, especially for individual investors, broadly reflecting our findings from Panel A of Table 6. The regression, in Panel B of Table 6, yields a magnitude on the jackpot dummy coefficient of -7.1% (p-value of 0.032). Probing further with the log of the turnover as a proxy for trading activity, we find, in Panel C of Table 6, an analogous effect, with a coefficient of -6.2% (p-value of 0.042). Our evidence corroborates that the documented impact of lottery on trading activity is likely an intrinsic property of our sample.[6]

Given that the decrease in trading value is five-fold larger than the large jackpot threshold of 500 million TWD, or equivalently three times larger than the conditional average (i.e, 840 million TWD) of jackpots above the threshold, the substitution effect between lottery and stock is predominantly about investor attention and not about reverse causation from the stock market to lottery sales.

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[5]There is some anecdotal evidence favoring our arguments. For instance, during the world cup soccer game between the U.S. and Algeria on June 24, 2010, the New York Stock Exchange experienced a 32% reduction in trading volume at 11:30 a.m., compared to its 10-day moving average at that hour (see http://www.cnbc.com/id/37897862).

[6]In general, there is a high correlation between trading by individual investors in the market and the total trading in the market. The respective correlations are 0.94, 0.85, and 0.92 for the shares traded, the value traded, and turnover.

4.6. Restricted samples impart a qualitatively similar picture

How robust are our results over restricted samples? Germane to this question is the feature that lottery drawings are not held every day. In particular, most Wednesdays do not have a lottery drawing.

To investigate the influence of any day-of-the-week patterns on our results, we modify our empirical specification (1) to exclude those trading days that do not have lottery drawings. We focus on stock types with high individual trading fraction, low market capitalization, high return volatility, and high return skewness to save on space, and also because they are representative of our results. Panel A of Table 7 conveys the fundamental point that our findings are unchanged, with the understanding that a large jackpot could happen in any day of the week except for Wednesday, thereby minimizing the concern of other day-of-the-week patterns.

Panel B of Table 7 reports the estimation results for our daily sample over the years 2002 to 2005, confirming a qualitatively similar negative lottery impact on stock trading. Although a slightly stronger substitution effect is detected, it is likely driven by the novelty of lottery over the years 2002 to 2005. Collectively, the documented relation between lottery and trading activity appears structurally stable and is not an artifact of the sample.

5. Concluding remarks

In this paper, we take advantage of multiple natural experiments of large jackpot lotteries in Taiwan, and our empirical specifications yield results that are consistent with the notion that buying lottery with a large jackpot can be a substitute for stock trading. We establish five distinct empirical findings.

First, when the jackpot exceeds 500 million Taiwan dollars (about 15 million U.S. dollars), the number of shares traded by individual investors decreases by about 7% among stocks with high individual trading fraction, low market capitalization, high past returns, and high past turnover. For stocks with low individual trading fraction, high market capitalization, low past returns, and low past turnover, the effect of lottery on trading activity is statistically indistinguishable from zero. Second, our approach reveals that the substitution effect is stronger among stocks with lottery features.

Specifically, a 9% decline in shares traded is observed among stocks with high return volatility and skewness. Third, consistent with our hypothesis, we also find that the magnitude of the documented substitution effect increases monotonically with the jackpot. Fourth, the reaction of firm-level trading activity by individual investors is negative to lottery drawings, and is statistically significant for a sizable number of firms. Finally, the aggregate number of shares traded by individual investors declines by 6% with lottery offerings, and this effect is both economically and statistically significant. We attribute the substitution effect to two features of large jackpots: one, they attract individual investor attention and, two, they satisfy their behavioral trading needs, such as entertainment, sensation seeking, and gambling.

A large jackpot lottery can be regarded as a natural experiment because it is a pure outcome of probability, and it is independent of the stock market. In addition, Taiwan has high individual investor participation in the stock market and no other legal gambling venues. This makes Taiwan a convenient setting to investigate the substitution between lottery buying and stock trading.

We contribute to the growing literature of individual investor trading along two dimensions. First, we offer market-wide evidence on why individual investors trade, which is as important as the evidence using individual investor data. Second, our natural experiments help to minimize the concern of endogeneity and show that individual investors trade for behavioral reasons similar to those for buying large jackpot lotteries.

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Table 1 Lottery jackpot size descriptive statistics

Year	Number of lottery drawings	Number of drawings (jackpot $\geq$ 500 m)	Mean	Std.	Min.	50th percentile	90th percentile	Max.
			Jackpot size (in millions of TWD)					
All years	1,495	163	255	267	23	178	529	2,930
2002	99	27	470	238	284	379	698	1,823
2003	104	11	341	182	195	287	522	1,329
2004	209	16	257	238	84	198	430	2,097
2005	208	14	218	220	65	149	431	1,732
2006	248	15	183	283	42	88	378	2,930
2007	209	11	147	202	23	77	369	1,799
2008	209	37	317	361	27	195	770	2,138
2009	209	32	276	216	32	198	599	1,209

Notes. Reported are the descriptive statistics for the lottery jackpot from January 22, 2002, to December 31, 2009. There are a total of 1,495 lottery drawings, and reported values are in millions of Taiwan dollars (TWD). Reported also are the number of lottery drawings with a jackpot larger than 500 million TWD and the number of lottery drawings with a jackpot larger than 500 million TWD on a trading day. Displayed are mean, standard deviation (denoted Std.), minimum (denoted Min.), 50th percentile, 90th percentile, and maximum (denoted Max.) of the jackpot.

Table 2 Stock market daily trading activity statistics

Year	Number of shares traded, total (in mil.)	Number of shares, individuals (in mil.)	Value of shares traded (mil., TWD)	Number of transac.	Market turnover (%)	Individual turnover (%)	Market cap. (in bil.)	Stock price (TWD)	Sales over value (%)
All years	3,024	1,948	90,448	678,503	0.61	0.39	14,119	21	0.20
2002	2,808	2,128	72,660	578,506	0.77	0.58	9,546	18	0.97
2003	3,118	2,267	74,898	583,779	0.74	0.55	10,538	18	0.65
2004	3,192	2,179	79,548	594,266	0.68	0.47	13,083	18	0.36
2005	2,370	1,427	70,876	506,772	0.48	0.29	13,863	18	0.29
2006	2,596	1,554	90,459	601,242	0.49	0.30	16,168	24	0.15
2007	3,323	2,050	126,662	830,838	0.61	0.37	21,024	32	0.08
2008	2,958	1,544	99,354	781,058	0.52	0.27	18,658	27	0.12
2009	4,009	2,769	116,257	1,067,770	0.69	0.47	17,024	27	0.11

Notes. Reported are the daily statistics on the Taiwan Stock Exchange (TSE) from January 1, 2002, to December 31, 2009. All variables are the *medians* of daily values. The "Number of transactions" is the number of trades recorded on the TSE tapes. The "Market turnover" is the number of shares traded divided by the number of shares outstanding on the TSE. Further, "Individual turnover" is the number of shares traded by individual investors divided by the number of shares outstanding. Following convention, "Market cap." is the total stock market capitalization (shares outstanding multiplied by price) in billions of TWD, while "Sales over value" is lottery sales divided by the value of shares traded.

Table 3 Impact of large jackpot on number of shares traded in stocks favored by individual investors

Dependent variable: Log of shares traded by individual investors	Large jackpot dummy	Trading activity $[-4 \rightarrow -25]$	Intercept	$\overline{R}^2$ $\lfloor DW \rfloor$	Joint p-val.
Panel A: Individual trading fraction stocks					
High individual trading fraction stocks	−0.072	0.865	1.683	61.6%	0.000
	(0.030)	(0.000)	(0.000)	$\lfloor 0.4 \rfloor$	
Low individual trading fraction stocks	−0.022	0.831	2.261	47.8%	0.000
	(0.509)	(0.000)	(0.000)	$\lfloor 0.7 \rfloor$	
Panel B: Market capitalization					
High market cap stocks	−0.045	0.843	2.174	52.3%	0.000
	(0.145)	(0.000)	(0.000)	$\lfloor 0.6 \rfloor$	
Low market cap stocks	−0.078	0.880	1.421	64.8%	0.000
	(0.032)	(0.000)	(0.000)	$\lfloor 0.4 \rfloor$	
Panel C: Past returns					
High past return stocks	−0.115	0.833	2.248	55.2%	0.000
	(0.004)	(0.000)	(0.000)	$\lfloor 0.5 \rfloor$	
Low past return stocks	0.028	0.642	4.669	22.6%	0.000
	(0.424)	(0.000)	(0.000)	$\lfloor 0.6 \rfloor$	
Panel D: Past turnover					
High past turnover stocks	−0.071	0.819	2.509	48.0%	0.000
	(0.011)	(0.000)	(0.000)	$\lfloor 0.7 \rfloor$	
Low past turnover stocks	−0.057	0.856	1.641	58.2%	0.000
	(0.210)	(0.000)	(0.000)	$\lfloor 0.5 \rfloor$	

Notes. Estimation results are based on the specification $\log(V_{p,t}) = \beta_0 + \beta_{p,1} D_t^{Jackpot} + \beta_{p,2} \log(\overline{V}_{p,[t-4 \rightarrow t-25]}) + \varepsilon_{p,t}$, for $p = H, M, L$. The dependent variable is the log of the shares traded and the "large jackpot dummy" equals one if the jackpot size exceeds 500 million TWD. We measure the number of shares traded by individual investors in four ways, respectively, as (i) individual trading fraction, (ii) market capitalization, (iii) past returns, and (iv) past turnover. Each day, we divide the ordered distribution of stocks by the characteristic into three parts, each respectively representing 30%, 40%, and 30% of the sample, based on their average value over day $t - 4$ to $t - 25$. The two-sided p-values (reported in parenthesis) are calculated using the Newey and West (1987) heteroscedasticity and autocorrelation consistent (HAC) covariance matrix estimator with lag length set to 7 (computed as the number of daily observations, 1,989, raised to the power 1/4). $\overline{R}^2$ is adjusted R^2, and the Durbin Watson statistic is shown as $\lfloor DW \rfloor$. We report the p-values for the null hypothesis that all the regression coefficients are jointly equal to zero.

Table 4 Impact of large jackpot on number of shares traded by individual investors for stocks with lottery features

Dependent variable: Log of shares traded by individual investors	Large jackpot dummy	Trading activity $[-4 \rightarrow -25]$	Intercept	$\overline{R}^2$ $\lfloor DW \rfloor$	Joint p-val.
Panel A: Return volatility					
High return volatility stocks	−0.091	0.848	2.076	53.2%	0.000
	(0.001)	(0.000)	(0.000)	$\lfloor 0.6 \rfloor$	
Low return volatility stocks	−0.028	0.836	2.004	53.0%	0.000
	(0.519)	(0.000)	(0.000)	$\lfloor 0.5 \rfloor$	
Panel B: Return skewness					
High return skewness stocks	−0.094	0.827	2.190	52.6%	0.000
	(0.016)	(0.000)	(0.000)	$\lfloor 0.5 \rfloor$	
Low return skewness stocks	−0.064	0.886	1.512	62.1%	0.000
	(0.051)	(0.000)	(0.001)	$\lfloor 0.6 \rfloor$	

Notes. Estimation results are based on the specification $\log(V_{p,t}) = \beta_0 + \beta_{p,1} D_t^{Jackpot} + \beta_{p,2} \log(\overline{V}_{p,[t-4 \rightarrow t-25]}) + \varepsilon_{p,t}$, for $p = H, M, L$. The dependent variable is the log of the shares traded and the "large jackpot dummy" equals one if the jackpot size exceeds 500 million TWD. We measure the number of shares traded by individual investors in stocks with lottery features in two ways, respectively, as (i) return volatility, and (ii) return skewness. Each day, we divide the ordered distribution of stocks by the two lottery features into three parts, each respectively representing 30%, 40%, and 30% of the sample. Return volatility is calculated based on the past 22 trading day returns (following Campbell, Lettau, Malkiel, and Xu (2001)), while return skewness is calculated over the past six months (i.e., following Kumar (2009b)). The two-sided p-values (reported in parenthesis) are calculated using the Newey and West (1987) heteroscedasticity and autocorrelation consistent (HAC) covariance matrix estimator with lag length set to 7 (computed as the number of daily observations, 1,989, raised to the power 1/4). $\overline{R}^2$ is adjusted R^2, and the Durbin Watson statistic is shown as $\lfloor DW \rfloor$. We report the p-values for the null hypothesis that all the regression coefficients are jointly equal to zero.

Table 5 Impact of large jackpot on the number of shares traded, firm-level evidence

		Restricted $\beta_{3,i} \equiv 0$	Unrestricted model
Large jackpot lottery dummy	Avg.	−0.078	−0.076
	t-stat	(−19.52)	(−19.03)
	#, p-val. < 0.05	{109}	{107}
	#, p-val. < 0.10	{173}	{172}
Log of average firm's daily number of shares traded by individual investors over $[-4 \to -25]$	Avg.	0.831	0.795
	t-stat	(206.56)	(159.35)
	#, p-val. < 0.05	{728}	{729}
	#, p-val. < 0.10	{731}	{731}
Log of number of shares in market traded by individual investors over $[-4 \to -25]$	Avg.		0.156
	t-stat		(16.67)
	#, p-val. < 0.05		{285}
	#, p-val. < 0.10		{339}
$\overline{R}^2$, Avg		42.9%	43.5%
Number of firms		734	734

Notes. The dependent variable is the log of the firms' number of shares traded by individual investors, $\log(V_{i,t}) = \beta_{0,i} + \beta_{1,i} D_t^{Jackpot} + \beta_{2,i} \log(\overline{V}_{i,[t-4 \to t-25]}) + \beta_{3,i} \log(\overline{V}_{m,[t-4 \to t-25]}) + \varepsilon_{i,t}$, for $i = 1,\ldots,I$. The large jackpot lottery dummy corresponds to a cumulative prize in excess of 500 million TWD. We control for the firm's average trading, and the market average trading, during $[-4 \to -25]$ prior to the lottery drawing day. Reported are (i) average of the estimated coefficients, (ii) t-statistic on the average coefficient, under the assumption that the coefficients are distributed i.i.d, and (iii) #, p-val. < 0.050 (and #, p-val. < 0.100), which corresponds to the number of coefficients with p-value less than 0.050 (0.100), and with a sign that is of the average coefficient; these are reported in curly brackets, and are based on the Newey and West heteroscedasticity and autocorrelation consistent (HAC) covariance matrix estimator.

Table 6 Impact of large jackpot on the aggregate trading behavior

| Dependent variable	Large jackpot dummy	Corresponding trading activity over $[-4 \rightarrow -25]$	Intercept	$\overline{R}^2$ $\lfloor DW \rfloor$	Joint p-val.
Panel A: Log of shares traded					
Log of shares traded by individuals	-0.060	0.840	2.300	53.3%	0.000
	(0.050)	(0.000)	(0.000)	$\lfloor 0.6 \rfloor$	
Panel B: Log of value traded					
Log of value traded by individuals	-0.071	0.884	2.026	60.4%	0.000
	(0.032)	(0.000)	(0.000)	$\lfloor 0.6 \rfloor$	
Panel C: Log of turnover					
Log of turnover by individuals	-0.062	0.864	-0.140	60.4%	0.000
	(0.042)	(0.000)	(0.000)	$\lfloor 0.6 \rfloor$	

Notes. Here we perform the regression: $V_{m,t} = \beta_0 + \beta_1 D_t^{Jackpot} + \beta_2 \overline{V}_{m,[t-4 \rightarrow t-25]} + \varepsilon_t$, where $V_{m,t}$ is either the log of shares traded in the aggregate (Panel A), the log of the total value traded (Panel B), or the log of the turnover (Panel C), all by individual investors. The "large jackpot dummy" equals one if the jackpot size exceeds 500 million TWD. $\overline{V}_{m,[t-4 \rightarrow t-25]}$ is the average trading of individual investors in the market during $[-4 \rightarrow -25]$ prior to the lottery drawing day. The two-sided p-values (reported in parenthesis) are calculated using the Newey and West (1987) heteroscedasticity and autocorrelation consistent (HAC) covariance matrix estimator with lag length set to 7. $\overline{R}^2$ is adjusted R^2 and the number of daily observations used in each estimation is 1,989. The Durbin Watson statistic is shown as $\lfloor DW \rfloor$. We report the p-values for the null hypothesis that all the regression coefficients are jointly equal to zero.

Table 7 **Impact of large jackpot on trading behavior when sample is restricted to lottery drawing days only, and the 2002–2005 subsample**

Dependent variable	Large jackpot dummy	Corresponding trading activity over $[-4 \rightarrow -25]$	Intercept	$\overline{R}^2$ $\lfloor DW \rfloor$	Joint p-val.
Panel A: Sample restricted to lottery drawing days only					
High individual trading fraction	−0.072	0.866	1.663	62.0%	0.000
	(0.040)	(0.000)	(0.000)	$\lfloor 0.6 \rfloor$	
Low market cap	−0.076	0.888	1.316	66.2%	0.000
	(0.051)	(0.000)	(0.002)	$\lfloor 0.5 \rfloor$	
High return volatility	−0.091	0.862	1.872	54.3%	0.000
	(0.002)	(0.000)	(0.000)	$\lfloor 0.8 \rfloor$	
High return skewness	−0.101	0.828	2.183	54.3%	0.000
	(0.014)	(0.000)	(0.000)	$\lfloor 0.6 \rfloor$	
Panel B: 2002–2005 subsample					
High individual trading fraction	−0.131	0.818	2.231	54.9%	0.000
	(0.002)	(0.000)	(0.000)	$\lfloor 0.5 \rfloor$	
Low market cap	−0.105	0.848	1.789	59.6%	0.000
	(0.011)	(0.000)	(0.002)	$\lfloor 0.5 \rfloor$	
High return volatility	−0.095	0.851	2.031	52.9%	0.000
	(0.011)	(0.000)	(0.002)	$\lfloor 0.7 \rfloor$	
High return skewness	−0.109	0.813	2.354	50.0%	0.000
	(0.025)	(0.000)	(0.001)	$\lfloor 0.6 \rfloor$	

Notes. Estimation results are based on the specification $\log(V_{p,t}) = \beta_0 + \beta_{p,1} D_t^{Jackpot} + \beta_{p,2} \log(\overline{V}_{p,[t-4 \rightarrow t-25]}) + \varepsilon_{p,t}$, for $p = H, M, L$. The dependent variable is the log of the shares traded by individual investors. Panel A reports results for the sample restricted to lottery drawing days only, while Panel B restricts the sample to the initial sample period of January 22, 2002, to December 31, 2005. The "large jackpot dummy" equals one if the jackpot size exceeds 500 million TWD. The two-sided p-values (reported in parenthesis) are calculated using the Newey and West (1987) heteroscedasticity and autocorrelation consistent (HAC) covariance matrix estimator. The lag length is set to 7 in Panel A and is set to 6 in Panel B to account for the smaller sample size of 994. $\overline{R}^2$ is adjusted R^2, and the Durbin Watson statistic is shown as $\lfloor DW \rfloor$. We report the p-values for the null hypothesis that all the regression coefficients are jointly equal to zero.
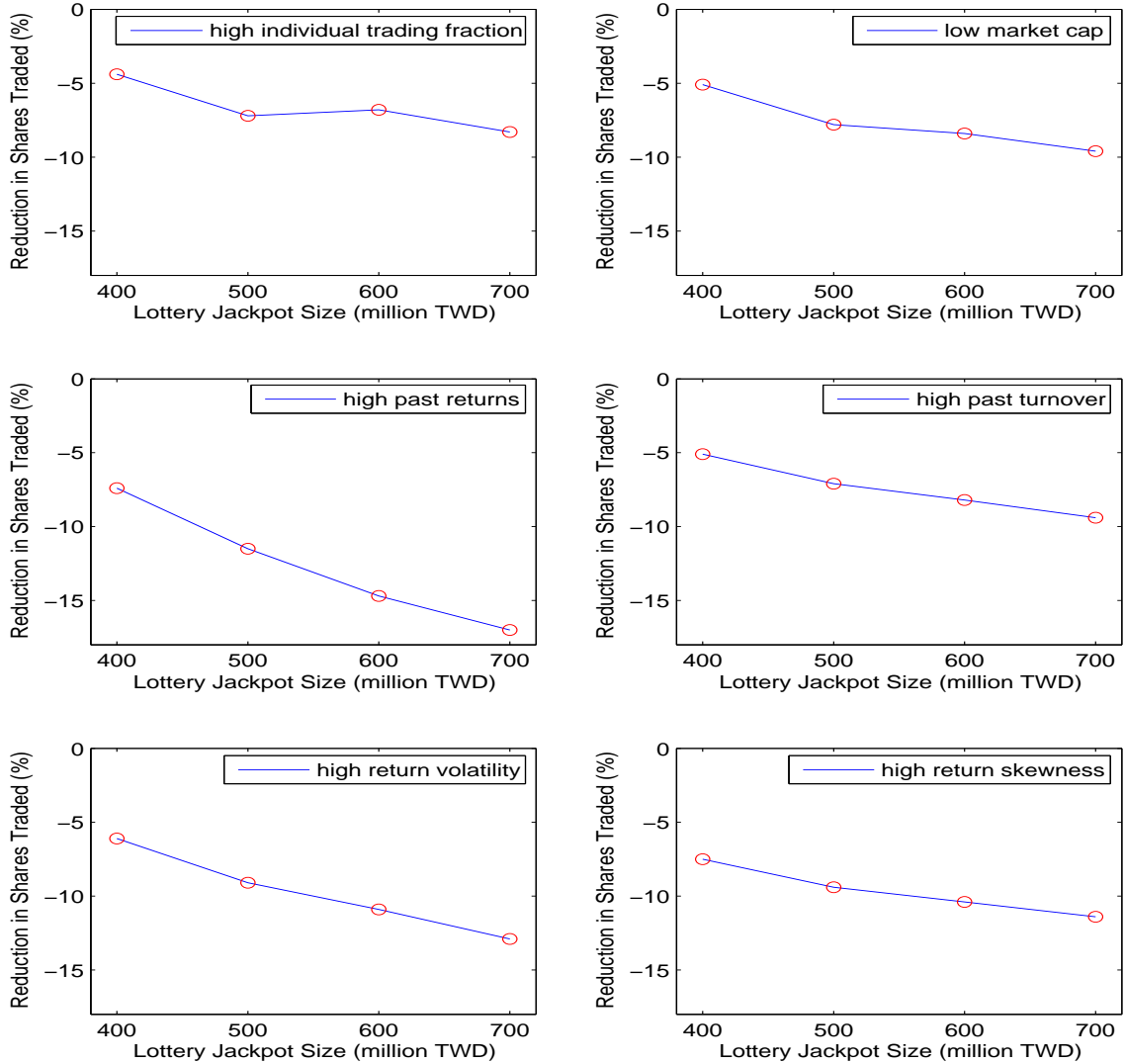
Figure 1 Size of the lottery jackpot and its impact on shares traded

Note: Plotted is the coefficient on the jackpot dummy (on the *y*-axis) versus the size of the jackpot (on the *x*-axis), shown separately for stock portfolios sharing (i) high individual trading fraction, (ii) low market capitalization, (iii) high past returns, (iv) high past turnover, (v) high return volatility, and (vi) high (positive) return skewness. The size of the jackpot is allowed to vary from 400 million TWD to 700 million TWD. The coefficients are obtained from the regressions, $\log(V_{p,t}) = \beta_0 + \beta_{p,1} D_t^{Jackpot} + \beta_{p,2} \log(\overline{V}_{p,[t-4\to t-25]}) + \varepsilon_{p,t}$, where $V_{p,t}$ is the number of shares traded, and $\overline{V}_{p,[t-4\to t-25]}$ is the average number of shares traded daily over $[t-4 \to t-25]$.