Who Gambles In The Stock Market?

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ABSTRACT

This paper examines whether socio-economic and psychological factors which are known to influence lottery purchases lead to excess investment in lottery-type stocks. The results indicate that, unlike institutional investors, individual investors prefer stocks with lottery-type features. The demand for lottery-type stocks increases during bad economic times and such demand shifts influence the returns of lottery-type stocks. In the cross-section, factors which induce greater expenditure in lotteries also induce greater investment in lottery-type stocks – poor, young men who live in urban, Republican dominated regions and belong to specific minority (African-American and Hispanic) and religious (Catholic) groups invest more in lottery-type stocks. Additionally, investors who exhibit stronger preference for lottery-type stocks experience greater mean under-performance. Collectively, the evidence indicates that people's attitudes toward gambling are reflected in their stock investment choices and stock returns.

Hope springs eternal in the human breast.

– Alexander Pope, An Essay on Man.

The next best thing to a fortune is the chance of a fortune.

– Chance, New Statesman and Nation, June 6, 1931.

Lottery participation is quite widespread in the United States (e.g., Welte, Barnes, Wieczorek, Tidwell, and Parker (2002), Jones (2004)). The extant evidence suggests that lottery participation rates and levels of lottery purchases are strongly influenced by a variety of socio-economic and psychological factors. Poor individuals tend to spend a greater proportion of their income on lottery purchases (e.g., Clotfelter and Cook (1989), Clotfelter (2000), Rubinstein and Scafidi (2002)) and their demand for lottery increases with a decline in their income (Blalock, Just, and Simon (2004)). In addition to wealth, age and education

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level influence lottery purchases – younger and less educated individuals find lotteries more attractive. Furthermore, relative to women, men are more likely to participate in lotteries while single or divorced individuals are more likely to participate in lotteries than people who are married.

Previous studies have also documented that race, ethnicity, religion, and political affiliation influence attitudes toward lottery-playing and gambling. Lottery participation rates and purchase levels are higher among African-American and Hispanic minority groups (e.g., Herring and Bledsoe (1994), Price and Novak (1999)). Among religious groups, Catholics and Jews participate in lotteries more than Protestants and Mormons (e.g., Grichting (1986), Clotfelter and Cook (1989)). And lastly, there is an effect of geographical location on lottery purchases – urban people are more likely to buy lotteries than people located in rural areas.

Taken together, the results from lottery studies indicate that the heaviest lottery players are poor, young, and uneducated single men who live in urban areas and belong to specific minority (African-American and Hispanic) and religious (Catholic) groups. Do individuals with these characteristics also exhibit a strong preference for lottery-type stocks when they invest in the stock market? And why would their preferences for lotteries spillover into the stock market? Because common biological, psychological, religious, and socio-economic factors jointly determine the "make-up" of a gambler (e.g., Walker (1992)), it is quite conceivable that individuals with preference for lotteries would adopt a gambling mindset in other domains of their lives. In particular, people's investment choices may be influenced by their attitudes toward lottery-playing and gambling.[1]

Individuals are likely to find lotteries and lottery-type stocks attractive for several reasons. Lotteries are likely to give people, especially those who are poor, a hope for a better life. For a very low cost, they may dream about becoming rich (e.g., Pope (1983), Simon (1998)).[2] These people may be fully aware that lotteries have negative expected payoffs, but nonetheless, they may exhibit a preference for lotteries because a remote chance of winning is perceived to be better than no chance of winning at all. Apart from this wishful thinking, there may also be an element of "thrill" involved with lottery purchases. However, Blalock,

[1]Strictly speaking, gambling, lottery-playing, and speculation are related but distinct activities. *Speculation* refers to an activity where a risk-seeking (or a less risk averse) individual takes relatively larger bets with large risks and gets rewarded appropriately. Under this definition of speculation, one can define speculative stocks as those which have higher variance and higher expected returns. In contrast, *gambling* refers to the activity where an individual takes large risks but the reward is not commensurate with the level of risk taken (i.e., expected payoff or return is negative). Gamblers still undertake such bets because they derive utility from the "thrill" of being in a risky situation. In other words, gamblers are likely to trade lower returns for the utility they derive from the "thrill" of gambling. Lastly, *lotteries* are distinct from speculative and gambling activities. When an individual buys a lottery, she spends a small amount of money and expects to earn a low negative return with a high probability and a large positive return with a very small probability. Lottery players are willing to accept a negative expected return for the possibility of a large positive payoff (i.e., hitting the jackpot). Under this characterization of lotteries, stocks with lottery-type features would have lower prices, higher volatility, and large positive skewness.

[2]The role of anticipatory utility such as dream utility has been recognized in other contexts. See Loewenstein (1987) and Caplin and Leahy (2001) for a formal treatment and Elster and Loewenstein (1991) for a rich but an informal discussion.

Just, and Simon (2004) find that entertainment motives do not seem to be the primary determinant of lottery participation decisions among the poor. Consistent with the predictions of earlier studies (e.g., Friedman and Savage (1948), Markowitz (1952), Kahneman and Tversky (1979)), they find that the lottery purchases of the poor are influenced by a strong desire to escape poverty and a strong yearning (relative to rich individuals) to rise in the social status.

If a desire to escape poverty induces gambling, socio-economic factors which promote lottery purchases are also likely to induce investors to adopt sub-optimal stock investment strategies. Specifically, investors with a large differential between their existing economic conditions and their aspiration levels would tilt their portfolios toward riskier lottery-type stocks. However, these investors may hold riskier stocks not necessarily because they are risk-seeking but rather because they want to have a positive probability, albeit very small, of reaching their aspiration levels. As Markowitz (1952) puts it aptly, some investors may "take large chances of a small loss for a small chance of a large gain."

Higher participation rates and excess expenditures in lotteries and lottery-type stocks may also be induced by individuals' inability to accurately perceive very small probabilities. Because people do not encounter extremely small probabilities such as 10^{-6} in their regular lives, they may over-weight the reward probabilities (e.g., Tversky and Kahneman (1992)). Furthermore, over-weighting of low probabilities can induce a preference for skewness (Polkovnichenko (2005), Barberis and Huang (2005)) and given the positively skewed payoffs of lotteries (and lottery-type stocks), the attractiveness of lotteries (and lottery-type stocks) is likely to increase. Alternatively, people may choose to ignore those small probabilities and focus primarily on the size of the reward (e.g., Pope (1983), Forrest, Simmons, and Chesters (2002), Garrett and Sobel (2002)).[3] It is well-known that lotteries with larger jackpot sizes are more popular among lottery players, even though the odds of winning are extremely low. The larger the size of the jackpot, the more people are willing to ignore the high probability of losing. The fixation on the size of the jackpot may be further reinforced by the widespread coverage of jackpot winners in the media. Similarly, stocks with extreme returns, especially those which garner attention of the media due to their extreme returns, may be favored by investors who exhibit a preference for lotteries.

In addition to stock characteristics, investor characteristics may influence probability distortions, where relatively sophisticated investors are less likely to distort the probabilities. For instance, educated individuals are more likely to understand the odds of winning while

[3]Damasio (1994) and Loewenstein, Weber, Hsee, and Welch (2001) suggest that a very small probability of a positive event is sufficient to generate positive anticipatory emotions. Consequently, in risky situations, people may focus exclusively on the possibility rather than on the probability of outcomes. Furthermore, probabilities (even very small ones) can influence the decision frame chosen by people (Elster and Loewenstein (1991)). For instance, a gamble with a 100% chance of a moderate loss is obviously perceived as being unfavorable. However, with a small probability (say 0.01) of a large gain, the gamble may be framed as one where there is a 1% chance of a win (a positive frame) rather than a gamble where there is a 99% chance of a loss (a negative frame). The choice of a positive frame is likely to exacerbate the positive anticipatory emotions.

relatively less educated individuals may significantly distort the winning odds. If education is correlated with income and wealth, rich individuals are less likely to participate in lotteries. Even when they participate, they are likely to spend a relatively lower proportion of their income on lottery purchases. In a similar vein, wealthy investors may hold large equity portfolios but they are likely to spend a relatively lower proportion of their wealth on lottery-type stocks.

What types of stocks are likely to be perceived as lotteries? Lottery tickets have very low prices relative to the highest potential payoff (i.e., the size of the jackpot), they have negative expected returns, their payoffs are very risky (i.e., the prize distribution has extremely high variance), and they have an extremely small probability of a very high reward, i.e., they have positively skewed returns. Mapping these lottery features onto stocks, I identify lottery-type stocks.[4] I *assume* that investors are more likely to perceive lower-priced stocks with very small but positive potential for high returns as lotteries. I further assume that stocks with higher variance (or higher idiosyncratic volatility or large extreme returns) and positively skewed returns are likely to be perceived as high payoff potential stocks.[5]

Under these assumptions, I conjecture that people who find lotteries attractive are likely to invest disproportionately more in stocks with higher idiosyncratic volatility, higher skewness, and lower prices, even if those stocks have lower expected returns. Additionally, to maintain a small positive probability of a large gain, people may continue to follow gambling motivated investment strategies in spite of their persistent losses. I test this conjecture using the end-of-month portfolio-holdings of a group of individual investors at a large U.S. brokerage house for the period 1991 to 1996. Specifically, I examine whether socio-economic and psychological factors which are known to influence lottery purchases lead to excess investment in lottery-type stocks.

My empirical analysis focuses on four distinct issues. First, I examine whether individual investors as a group prefer stocks with lottery-type features and compare individual preferences with institutional preferences. Second, I examine whether the demand for lottery-type stocks varies with broad economic conditions and whether such demand shifts influence the

[4] Lottery-type stocks are similar to penny stocks (stock price < \$1), pink sheets, and over-the-counter bulletin board stocks. However, because I define lottery-type stocks using multiple price- and return-based stock attributes, not all penny stocks, pink sheets, and bulletin board stocks would be classified as lottery-type stocks.

[5] Note that I am not suggesting that investors actively examine the moments of return distributions and formulate their portfolio decisions using these moments. Rather, I use the return moments-based characterization of lottery-type stocks to abstract away from a large number of behavioral mechanisms which are likely to generate a preference for higher order moments. For instance, as mentioned earlier, over-weighting of low probability events (e.g., the probability of winning a lottery jackpot) can induce a preference for skewness (Tversky and Kahneman (1992), Polkovnichenko (2005), Barberis and Huang (2005)). Brunnermeier and Parker (2004) show that anticipatory utility (e.g., dream utility) can generate a preference for skewness in portfolio choices. Alternatively, lottery-type stocks may have one or more salient characteristics (based on returns or the fundamentals) which investors may use to select stocks. For instance, positively skewed stocks with extreme returns may catch investors' attention (Barber and Odean 2005) or they may choose stocks based on salient attributes such as dividend-paying versus non-dividend-paying (Baker and Wurgler (2004), Baker and Wurgler (2005)) which may lead to a preference for lottery-type stocks.

returns of lottery-type stocks. Third, I investigate the cross-sectional differences in gambling motivated investment choices of investors across various demographic categories. I focus on the behavior of poor investors but I also examine the role of age, gender, race, ethnicity, religion, political affiliation, and location (i.e., rural versus urban) on investors' propensity to invest in lottery-type stocks. Finally, I using several performance benchmarks, I examine the relative portfolio performance of investors who invest in lottery-type stocks.

The notion that gambling motives may influence investment decisions is not entirely new. Previous studies (e.g., Friedman and Savage (1948), Markowitz (1952), Shefrin and Statman (2000), Shiller (2000, pp. 40-42), Statman (2002)) have emphasized the role of gambling behavior in the context of investment decisions. What is new in my paper is the formalization of the notion of lottery-type stocks and the direct evidence of cross-sectional variation in investors' preferences for lottery-type stocks. Previous studies have identified skewness preferences of investors as a determinant of portfolio under-diversification (e.g., Goetzmann and Kumar (2004), Mitton and Vorkink (2004)) but they do not examine the link between gambling attitudes and stock investment decisions which is the main focus of my paper.[6]

My results indicate that individual investors invest disproportionately more in stocks with higher idiosyncratic volatility, higher skewness, and lower prices even when these stocks have lower mean returns. These preferences are distinct from individual investors' known preferences (e.g., Barber and Odean (2000), Barber and Odean (2001), Kumar (2003)) for certain firm characteristics (e.g., small-cap stocks, value stocks, etc.). For robustness, I compare aggregate individual and institutional preferences and find that institutional investors prefer stocks with higher mean returns, lower idiosyncratic volatility, lower skewness, and higher prices. Individual investors' demand for lottery-type stocks increases when economic conditions are poor and those demand shifts influence the returns of lottery-type stocks.

Examining cross-sectional differences within the individual investor category, I find that socio-economic and psychological factors which induce higher expenditures in lotteries also induce greater investments in lottery-type stocks – poor, young men, who live in urban areas and belong to specific minority groups (African-American and Hispanic) invest more in stocks with lottery-type features. Additionally, investors who live in regions with higher concentration of Catholics (Protestants) have a stronger (weaker) preference for lottery-type stocks. I also find that investors who live in regions which voted strongly Republican (Democratic) in 1992 and 1996 presidential elections have a stronger (weaker) preference for lottery-type stocks.[7]

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[6] In a recent study, Malloy and Zhu (2004) examine whether investors in deprived neighborhoods (i.e., regions with a greater concentration of African-Americans, people with low income, and relatively less education levels) face sub-optimal investment opportunity sets in their mutual fund choices. They use race/ethnicity as a proxy for investor sophistication while my focus is on the relation between race/ethnicity and gambling behavior.

[7] The investor database does not contain information about the race/ethnicity, religion, and the political affiliation of investors. Using auxiliary data sources, I obtain (noisy) measures of these identities. To

Examining the portfolio performance of investors who invest in lottery-type stocks, I find that their portfolios exhibit significant under-performance – the mean annual under-performance is roughly 5% of investors' annual household income, where the range is 2-32%. Investors in the lowest income group (annual income < \$15,000) have a mean annual under-performance of \$4,725 which is almost 32% of their annual income.[8] High-income investors (annual income > \$125,000) also have comparable annual under-performance (\$4,250) but this under-performance is a lower proportion (1.70%) of their mean annual income. Collectively, my results indicate that investors who are pre-disposed to playing lotteries also exhibit strong preferences for lottery-type stocks in their investment choices. More importantly, and sadly, poor investors, who can least afford to under-perform, experience the most severe under-performance from their gambling motivated investments.[9]

Even though the mean annual under-performance estimates are economically significant, one may argue that the gambling motivated investment patterns I document are not very surprising because the brokerage accounts I examine represent investors' "play money" accounts meant primarily for gambling and entertainment purposes. My results are robust to this concern because several pieces of evidence suggest that this is unlikely to be the case. For instance, Goetzmann and Kumar (2004) find that a typical portfolio is about 79% of investor's annual income and roughly 32% of an investor's total net-worth. This evidence indicates that, for most investors, the brokerage account is unlikely to be her play money account. Furthermore, if these accounts indeed represent investors' play money accounts,

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identify an investor's race/ethnicity, religion, and political affiliation, I assign her the racial/ethnic profile of her zipcode, the religious profile of her state, and a political profile based on the voting patterns in her county, respectively. So, strictly speaking, the race measure of an investor indicates the dominant race in her zipcode, the religious affiliation measure refers to the religious distribution of her state, and the political affiliation measure reflects the political tilt of her county. However, I avoid these lengthy and awkward descriptors and use broad racial/ethnic, religious, and political labels such as Hispanic investor, Catholic investor, Republican investor, etc.

[8] I do not have a precise estimate of investors' annual income. I only know that the income lies in one of the following nine categories: 0-15K, 15-20K, 20-30K, 30-40K, 40-50K, 50-75K, 75-100K, 100-125K, and above 125K. I use the upper limit of the income range to obtain the under-performance estimates as a proportion of the income. Following Ivković and Weisbenner (2005), I assign an annual income of \$250,000 to the highest income category.

[9] In spite of considerable losses incurred by investors, I am not implying that investors are necessarily being irrational. To determine whether investors are truly acting irrationally, one needs to clearly define an appropriate model of gambling and lottery-playing but that has not been an easy task. Whether gambling behavior and people's preferences for lotteries can be explained within the rational expected utility framework has been a matter of considerable debate. For instance, the expected utility framework with a non-concave utility function (e.g., Friedman and Savage (1948), Hartley and Farrell (2002)) or even concave utility function with indivisible expenditures (Kwang (1965)) or market imperfections (Kim (1973)) can explain gambling behavior within the rational paradigm. Gambling behavior and lottery-playing can also be explained if one allows non-monetary utilities (e.g., anticipatory or dream utility, entertainment utility, etc.) to enter the utility function directly (e.g., Conlisk (1993), Diecidue, Schmidt, and Wakker (2004)) or allow for the act of gambling to offer direct consumption value (e.g., Johnson, O'Brien, and Shin (1999)). Additionally, non-expected utility paradigms such as the rank-dependent utility framework (Quiggin (1982)) or the cumulative prospect theory (Tversky and Kahneman (1992)) can explain gambling and lottery-playing. Given these alternative explanations for gambling and lottery-playing, the behavior of investors may be rational relative to some benchmarks but irrational relative to others. For instance, if investors' investments in lottery-type stocks are motivated by their preferences for skewness and anticipatory emotions such as hope, they may be reasonably happy even if their portfolios under-perform various performance benchmarks.

it is more likely to be the case for investors who are relatively more wealthy. Under this scenario, the portfolios of wealthy investors would be tilted more toward lottery-type stocks. However, my findings are just opposite which indicate that concentration of play money accounts in the sample is unlikely to contaminate my findings.

The rest of the paper is organized as follows: in the next section, I compare the aggregate preferences of individual and institutional investors for lottery-type stocks. In Section II, I examine the cross-sectional differences in gambling motivated investment choices of investors across various demographic categories. In Section III, I develop a profile of stock market gamblers by rotating the point of view from the cross-section of stocks to the cross-section of investors. I also examine whether the demand for lottery-type stocks varies with broad economic conditions and whether such demand shifts influence the returns of lottery-type stocks. In Section IV, using different benchmarks, I evaluate the portfolio performance of investors who adopt gambling motivated investment strategies. Finally, I conclude in Section V with a summary of the main results and a brief discussion.

I. Aggregate Preferences for Lottery-Type Stocks

A. Data and Sample Characteristics

The data for this study consists of all trades and end-of-month portfolio positions of investors at a major U.S. discount brokerage house for the 1991-96 time-period. This database has been used in several studies including Odean (1998, 1999) and Barber and Odean (2000, 2001). There are a total of 77,995 households in the database of which 62,387 have traded in stocks. Investors hold and trade a variety of other securities including mutual funds, options, ADRs, etc. An average investor holds a 4-stock portfolio (median is 3) with an average size of \$35,629 (median is \$13,869). Fewer than 10% of the investors hold portfolios over \$100,000 and fewer than 5% of them hold more than 10 stocks. For a subset of households, demographic information such as age, income, location (zipcode), total net worth (i.e., wealth), occupation, marital status, family size, gender, etc. is available. Further details on the investor database are available in Barber and Odean (2000).

I enrich the individual investor database using data from three other auxiliary sources. First, to identify the racial/ethnic profile of investors in the sample, I measure the racial/ethnic composition of each zipcode using data from the 1990 U.S. Census.[10] For each zipcode, I compute the proportion of individuals in the following five groups: (i) White, (ii) Black, (iii) Asian, (iv) Hispanic, and (v) Others. Given the zipcode of each investor, I assign her the appropriate zipcode-level racial profile.

[10]The U.S. Census data are available at `http://www.census.gov/main/www/cen1990.html`.

Second, for each state, I identify the relative proportions of different religious denominations using the 2001 American Religious Identification Survey data.[11] In the data, Catholics are identified as one group. To identify Protestants, I group the following denominations into one category: Methodist, Lutheran, Presbyterian, Protestant, Pentecostal, Episcopalian, Baptist, and Anglican. Using each investor's zipcode, I assign the appropriate state-level religious profile to the investor.

Lastly, I obtain county-level voting data from the 1992 and the 1996 presidential elections to estimate the political affiliations of investors in my sample.[12] For each county, I compute the ratio of the number of votes to the Democratic party and the number of votes to the Republican party during the 1992 and 1996 presidential elections. I assign the average of the appropriate county-level ratios to investors who live in that county.

In addition to extensive data on individual investors, I obtain quarterly institutional holdings from Thomson Financial. These data contain the end of quarter stock holdings of all institutions that file form 13F with the Securities and Exchange Commission. Institutions with more than $100 million under management are required to file form 13F, and common stock positions of more than 10,000 shares or more than $200,000 in value must be reported. A detailed description of the institutional ownership data is available in Gompers and Metrick (2001).

Several other standard datasets are used in this study. I obtain analysts' quarterly earnings estimates from I/B/E/S summary files. For each stock in the sample, I obtain monthly prices, returns, and market capitalization data from CRSP and quarterly book value of common equity data from COMPUSTAT. I obtain the monthly time-series of the 3 Fama-French factors, the momentum factor, the NYSE size break-points, and the B/M break-points for each month from Ken French's data library.[13]

B. Aggregate Preferences for Lottery-Type Stocks: Non-Parametric Tests

To set the stage, I examine whether individual investors assign a greater weight to stocks with lottery-type features. First, I divide all stocks in the sample into sixteen categories using independent sorts along mean return, idiosyncratic volatility, skewness, and stock price dimensions. Stocks are assigned to the upper or the lower half along each of these four dimensions, and sixteen stock categories are obtained.[14] The return moments are calculated using past 60 months of data and the idiosyncratic volatility measure is the variance of the

[11] The main results from the survey are available at `http://www.gc.cuny.edu/studies/key_findings.htm`. Ideally, I would like to use a more disaggregate data (e.g., county or zipcode level data) on religious affiliation for the 1991-96 time-period. Unfortunately, to my knowledge, such a dataset is not publicly available.

[12] The county-level presidential voting data can be purchased from `http://www.uselectionatlas.org/`.

[13] Ken French's data library is available at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/`.

[14] Admittedly, this is a very coarse categorization but it results in a manageable and easy-to-interpret 16 stock categories instead of 81 (or 256) categories when three (or four) divisions are used along each dimension.

residual obtained by fitting a four-factor model to the monthly stock returns series over the past 60 months. Next, every month I compute the weight assigned to each of these sixteen stock categories in the aggregate individual investor portfolio. Finally, I obtain the sample-period averages of those stock category weights.

The average stock category weights are presented in Table I. The results indicate that individual investors prefer stocks with higher volatility, higher skewness, and lower prices. They assign a weight of 8.33% to stocks which have higher volatility, higher skewness, lower price, and lower mean return. If they had randomly chosen stocks, the weight in this stock category would have been only 0.74%.[15] In contrast, individual investors assign a considerably lower weight to stocks which have lower volatility, lower skewness, higher price, and higher mean return. The weight in the aggregate individual investor portfolio is 33.27% when the expected weight (according to the aggregate market portfolio) is 53.94%. The weight allocations in other stock categories are also consistent with individual investors' revealed preferences for lottery-type stocks. Collectively, the evidence indicates that individual investors have a strong preference for lottery-type stocks (i.e., stocks with lower mean returns, higher volatility, higher skewness, and lower price) and they exhibit an aversion for stocks with non-lottery features.

Because of the summing-up constraint, the aggregate institutional preferences for lottery-type stocks should be opposite of individual investor preferences.[16] To investigate whether this fundamental constraint holds, I examine the aggregate preferences of institutional investors. Following the procedure described above, I measure the average weights assigned by institutions to the sixteen moment and price based stock categories defined above. These results are also reported in Table I. Two clear patterns emerge. First, the relative distortions in the aggregate institutional portfolio are lower which indicate that institutional preferences across various stock categories are more evenly distributed. Second, as expected, institutions exhibit a preference (aversion) for stocks which individuals dislike (prefer). For instance, in the stock category which is most favored by individual investors (stocks with higher volatility, higher skewness, lower price, and lower mean return), institutions allocate a lower than expected weight – the aggregate institutional allocation is 0.28% where the expected weight is 0.74%. In contrast, in the stock category which is least favored by individual investors (stocks with lower volatility, lower skewness, higher price, and lower mean returns), institutions allocate a higher than expected weight – the aggregate institutional allocation is 57.79% where the expected weight is 53.94%.

Overall, the pattern of institutional allocations indicate that the summing-up constraint holds approximately. This evidence provides a simple robustness check for the basic results

[15] The expected stock category weight benchmark reflects the weight of the stock category in the aggregate market portfolio where the market portfolio is obtained by combining all CRSP stocks.

[16] The institutional data represent the shares owned only by institutions in the Thomson Financial institutional dataset which does not include institutional investors who hold less than 10,000 shares and under $200,000 in dollar value. Additionally, the individual data is not perfectly representative of the retail stockholders in the U.S. Consequently, the summing-up constraints are expected to hold only approximately.

on individual preferences. More importantly, the opposite institutional preferences suggest that the individual investor sample I examine is likely to approximate the behavior of retail stock-holders in the U.S. In other words, the reported results may not be specific to the sample of brokerage account investors but may generalize to the wider population of U.S. retail investors.

C. *Aggregate Preferences for Lottery-Type Stocks: Regression Tests*

The non-parametric test results provide initial evidence of gambling induced preferences of individual investors but the evidence does not reveal whether individual investors' moment preferences are distinct from their known preferences (e.g., (Barber and Odean 2000), Kumar (2003)) for certain stock characteristics such as size, book-to-market (B/M), etc. To distinguish between investors' preferences for stock characteristics and moment preferences and to examine their relative strengths, I estimate several cross-sectional regressions. In the regression specification, the excess weight assigned to a stock in the aggregate portfolio is the dependent variable and various stock characteristics and return moments are employed as independent variables.

To measure the collective preference of a group of investors for a given stock, first, I combine the portfolios of all investors in the group and construct an aggregate group-level portfolio. Next, I construct the aggregate market portfolio by combining all CRSP stocks. If investors in the group were to randomly select stocks, the weight of each stock in the group portfolio would be approximately equal to the weight of the stock in the aggregate market portfolio. However, a positive (negative) deviation from the expected weight would indicate that the group has a preference (aversion) for the given stock. I obtain the unexpected (or excess) portfolio weight allocated to stock i in month t using:

$$EW_{ipt} = \frac{w_{ipt} - w_{imt}}{w_{imt}} \times 100. \tag{1}$$

Here, w_{ipt} is the actual weight assigned to stock i in group portfolio p in month t and w_{imt} is the weight of stock i in the aggregate market portfolio in month t. The EW_{ipt} measure reflects the group-level preference for stock i in month t.

In the first regression specification, I use mean return, idiosyncratic volatility, skewness, kurtosis, and stock price as independent variables. As before, these measures are obtained using the monthly stock returns series over the past 60 months. The estimation is carried out using a panel regression specification with month fixed effects and the independent variables have been standardized so that the coefficient estimates can be directly compared.[17]

[17] To ensure that my results are robust to concerns about multi-collinearity, I compute the variance inflation factor (VIF) for each of the independent variables. VIF measures the degree to which an explanatory variable can be explained by other explanatory variables in a regression model. For explanatory variable

The regression estimates are presented in Table II (Column 1). Consistent with the findings from non-parametric tests, I find that individual investors assign a larger weight to stocks which have higher idiosyncratic volatility, higher skewness, and lower prices, even if these stocks have lower mean returns. For instance, a one standard deviation increase in the idiosyncratic volatility of a stock results in a 1.234% increase in its weight in the aggregate individual investor portfolio. Individual investors also exhibit a strong aversion to kurtosis, i.e., they dislike stocks with "fat tails." This finding, in conjuction with individual investors' preference for stocks with higher idiosyncratic volatility and positive skewness, suggest that individual investors are able to discriminate between upward and downward idiosyncratic volatility, where they dislike the latter.

In the second regression specification, I introduce the following control variables: (i) market beta, which is estimated using past 60 months of data, (ii) firm size, (iii) book-to-market ratio, (iv) short-term momentum (past one-month stock return), (v) longer-term momentum (past twelve-month stock return), and (vi) an S&P500 dummy. The estimation results (see Column 3) indicate that the coefficient estimates of mean return, volatility, skewness, and stock price are significant even in the presence of these control variables. Furthermore, the coefficient estimates of control variables have the expected signs. For instance, the coefficient estimate of *Firm Size* is strongly negative which indicates that, on average, individual investors exhibit a preference for small-cap stocks. Additionally, a positive coefficient of the *S&P500 Dummy* indicates that investors exhibit a preference for relatively more visible firms which are part of the S&P500 index. Overall, the regression estimates indicate that individual investors prefer *both* volatility and skewness while they exhibit an aversion for stocks with higher prices and higher kurtosis.[18]

As a robustness check, I compare aggregate individual preferences with aggregate institutional preferences. The panel regression estimates (with quarter fixed effects) for the aggregate institutional portfolio are also presented in Table II (Column 4). As expected, I find that the two investor groups exhibit almost diagonally opposite preferences. Unlike individual investors, institutions prefer stocks with higher mean returns, lower variance, lower skewness, and higher stock prices. Additionally, institutions prefer stocks with higher market capitalization and higher market beta. Many of these results on institutional preferences are consistent with the findings of Gompers and Metrick (2001) and Frieder and Subrahmanyam (2005). However, the evidence on aggregate skewness aversion of institutions is new and has not been documented before.

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i, $VIF_i = 1/(1 - R_i^2)$ where R_i^2 is the R^2 in the regression where explanatory variable i is used as a dependent variable and other explanatory variables are used as independent variables. As a rule of thumb, multi-collinearity is not of concern as long as $VIF < 2$. See Gujarati (2003, p. 351) for details. I find that the VIF is less than two for all independent variables, which suggests that multi-collinearity is not a major concern.

[18] A considerable number of investors (about 27%) are located in California. The strong preference of Californians for technology stocks may bias my results. To guard against this possibility, I re-estimate the cross-sectional regression after excluding investors who reside in California. The sub-sample coefficient estimates (available upon request) are very similar to the full-sample results.

II. Do Attitudes Toward Gambling Influence Stock Investment Decisions?

The panel regression estimates in the previous section reveal that collectively individual investors prefer lottery-type stocks. But how do their preferences vary cross-sectionally? As discussed earlier, lottery studies have documented that the heaviest lottery players are poor, young, and uneducated single men who live in urban, Republican dominated areas and belong to certain specific minority (African-American and Hispanic) and religious (Catholic) groups. Do investors with these characteristics also tilt their portfolios more strongly toward lottery-type stocks?

A. Preferences of the Poor and the Wealthy

Wealth (and income) has been identified as one of the strongest determinants of lottery purchases. According to the "desperation" hypothesis of gambling (e.g., Friedman and Savage (1948), Brenner and Brenner (1990), Blalock, Just, and Simon (2004)), people often buy lotteries to cope with financial stress where the proportional lottery expenditure increases as wealth/income decreases. People who are unable to reach their aspiration levels may resort to gambling when hope from other sources has dried out.[19] Lotteries provide a glimmer of hope to those people when all other avenues are closed. The following quote from a lottery player in Chicago's West Side accurately sums up this sentiment (Brodt (1986)):

> *I have dug so many holes for myself over the years that realistically, winning the lottery may be my only ticket out.*

If lottery purchases are driven by a deep desire to escape poverty, such preferences are likely to spillover to the investment arena. Consequently, poor investors are more likely to tilt their portfolios toward lottery-type stocks.

To identify differences in preferences of poor and rich investors for lottery-type stocks, I sort investors according to their wealth levels and construct three group-level portfolios. To construct portfolio 1 (portfolio of the poor), I combine the portfolios of all investors in wealth deciles 1-3. Portfolios 2 and 3 (portfolio of the rich) are constructed in an analogous manner by combining portfolios of investors in wealth deciles 4-7 and 8-10, respectively. Investors in the "poor" category have total net worth of $75,000 or below while investors in the "rich" category have total net worth of $200,000 and above.[20]

[19]A similar explanation has been put forth to explain criminal behavior. People who have no option to get out of the poverty trap may feel frustrated and ultimately resort to criminal activities. Crime is also like a gamble which has a small positive probability of a large gain but a moderate to high probability of a significant loss. There is evidence (e.g., McCorkle (2004)) that people who are addicted to gambling exhibit a greater propensity to engage in criminal activities.

[20]My results are not sensitive to the cutoffs employed to define "poor" and "rich" wealth categories. In fact, the results are stronger when I employ stricter wealth cutoffs (e.g., using wealth deciles) for identifying "poor" and "rich" categories. Additionally, even though wealth and income are not perfectly correlated, the results are very similar when I consider income sorted investor categories.

Following the procedure described in Section I.B, I examine whether poor individual investors assign a greater weight (relative to rich individual investors) to stocks with lottery-type features. The results are presented in Table III. Consistent with the desperation hypothesis of gambling, I find that poor individual investors exhibit stronger preference for lottery-type stocks. For instance, poor (rich) investors assign a 8.33% (7.69%) weight to stocks which have higher volatility, higher skewness, lower price, and lower mean return. The weight difference of 0.98% is statistically significant (p-value < 0.01). The differences in the preferences of poor and rich individual investors are not as distinct as the preference differentials between individual and institutional investors (see Table I). Nonetheless, these weight comparisons reveal that poor investor portfolios are tilted more toward lottery-type stocks.

To better understand the poor-rich preference differentials, I follow the panel regression procedure described in Section I.C and estimate four cross-sectional regressions, one for each of the three wealth sorted portfolios (poor, others, rich), and a fourth regression for the poor-rich portfolio differential. The differences in the preferences of poor and rich investors are likely to reveal themselves more clearly in these conditional models where several control variables are employed.

Table IV reports the regression estimates. Consistent with the non-parametric test results, I find that poor investors exhibit a significantly stronger preference (relative to rich investors) for stocks which have lower mean returns, higher idiosyncratic volatility, and higher skewness. The preference differential along idiosyncratic volatility dimension appears to be strongest – a one standard deviation increase in a stock's idiosyncratic volatility corresponds to a 1.275% higher increase in the weight assigned to the stock by poor investors. The difference in preferences along the stock price dimension is also significant but the magnitude of this differential is small. Additionally, I find that the kurtosis preference differential is significant which indicates that poor investors exhibit a stronger aversion to kurtosis. Lastly, coefficient estimates of control variables reveal that poor investors prefer lower capitalization stocks and also stocks which are in the S&P500 index. Collectively, the regression estimates indicate that poor investors invest disproportionately more than rich investors in stocks which have lottery-type features.

B. Age and Gambling Motivated Stock Investments

Lottery studies have also shown that attractiveness of gambling decreases with age. Younger and middle-aged people are more likely to participate in lotteries and they are also more likely to spend a greater proportion of their income on lotteries. The relation between age and gambling may reflect the composite effect of risk aversion, wealth, and aspiration levels. Younger people are likely to have lower risk aversion, lower wealth levels, and they are also likely to have higher aspiration levels.[21] In contrast, older people are likely to be more risk averse, they are likely to have accumulated greater wealth, and they may have adjusted their aspirations to their current levels. Consequently, older investors are less likely to gamble. Does age play a similar role in shaping investors' preferences for lottery-type stocks?

To examine whether age influences individual investors' preferences for lottery-type stocks, I follow the panel regression estimation procedure described earlier (see Sections I.C and II.A) and estimate cross-sectional regressions for age and wealth sorted investor groups. In the first set, I consider three age sorted portfolios for younger (age below 40), middle-aged (age between 40 and 65), and older (age above 65) investors, and a fourth regression for the younger-older differential.[22] In the second set, I consider age based portfolios within the poor investor category.

The regression estimates are reported in Table V, Panel A. For brevity, I only report the coefficient estimates of *Mean Return*, *Idiosyncratic Volatility*, *Skewness*, *Kurtosis*, and *Stock Price* variables. Consistent with the results from lottery studies, I find that younger and middle-aged investors exhibit stronger preference for stocks with lottery-type features. The *Idiosyncratic Volatility* coefficient estimate decreases with age and the *Skewness* coefficient estimates of younger and middle-aged groups are higher than that of the older investor group. When I examine the preferences across age groups after conditioning on wealth, the preferences of younger and middle-aged investors stand out more distinctly. I find that, within the group of poor investors, middle-aged investors exhibit the strongest preference for lottery-type stocks. Collectively, my findings on the relation between age and investment in lottery-type stocks are similar to the results documented in lottery studies.

C. Gender, Marital Status, and Gambling Motivated Stock Investments

Lottery studies portray single men as heavy gamblers. Several factors are likely to exacerbate gambling behavior in men. Men are likely to be less risk averse, they are likely to be more over-confident (e.g., Barber and Odean (2001)), and single men are likely to exhibit these attitudes more strongly. To examine whether gender and marital status influence investors' investment behavior, I follow the panel regression estimation procedure described earlier (see Sections I.C and II.A) and I estimate cross-sectional regressions corresponding to the aggregate portfolios of men, women, and men-women differential.

The regression estimates are reported in Table V, Panel B. Consistent with the findings from lottery studies, I find that men exhibit a stronger preference (relative to women) for lottery-type stocks. Additionally, investors who are single prefer lottery-stocks more than married investors. And single men exhibit a significantly stronger preference for lottery-

[21]In my sample, wealth increases with age. For instance, investors who are younger than 35 years have a mean net worth of $168,500 while investors who are 65 years or older have a mean net worth of $350,000.

[22]My results are not sensitive to the cutoffs employed to define the three age categories.

type stocks than single women. In fact, single women do not exhibit preference for stocks with positively skewed returns. Collectively, again, these findings are similar to the relation between gender, marital status, and gambling attitudes documented in lottery studies and surveys.

D. Religion, Race, Ethnicity, Political Affiliation, and Preference for Lottery-Type Stocks

Prior evidence from lottery studies indicate that racial, ethnic, religious, and political identities of individuals jointly determine their attitudes toward gambling. For instance, Protestants (especially the Baptist denomination) and Mormons are more likely to be opposed to gambling than Catholics and Jews (e.g., Grichting (1986), Clotfelter and Cook (1989)). Among Protestants who attend church regularly, 80% believe gambling is wrong and 95% of Protestant clergy believe gambling is immoral (Clotfelter and Cook (1989)).[23] Taken together, the extant evidence indicates that religious beliefs influence people's attitudes toward gambling.

The link between race, ethnicity, and gambling behavior has also been well-established (e.g., Herring and Bledsoe (1994), Price and Novak (1999), Clotfelter and Cook (1989, Chapter 6)). African-Americans and Hispanics are more likely to gamble and they are also more likely to be compulsive gamblers. Lastly, political affiliation is likely to influence attitudes toward gambling because the political affiliation of a person is likely to influence his or her ideology (i.e., conservative, liberal, or moderate) and the ideological tilt may influence gambling behavior.[24] Collectively, racial/ethnic, religious, and political identities of an investor are likely to capture elements of her risk aversion, education level, structure of the social network, ideological preferences, beliefs about morality of gambling, and socio-economic status.

In light of these findings, it is quite conceivable that racial, ethnic, religious, and political identities of investors would influence their stock investment decisions, particularly their decisions to invest in lottery-type stocks. To examine the influence of race, ethnicity, religion, and political affiliation on investors' investment choices, I estimate several cross-sectional regressions following the panel regression estimation procedure described earlier (see Sections I.C and II.A). First, I examine the influence of race and ethnicity. The results are reported in Table V, Panel C. I find that investors who are located in zipcodes with higher concentration of African Americans and Hispanics exhibit stronger preference for lottery-type stocks. Furthermore, when I condition on wealth and examine racial and ethnic

[23]The dates of adoption of state lotteries within the U.S. seem to have been influenced by people's religious beliefs – states which were early adopters of lotteries had a large Catholic population while states who were opposed to lotteries until 1988 had a disproportionately higher population of Baptists (Clotfelter and Cook (1989, pp. 147-148)). The states which were early adopters had a 33% average Catholic population and only 2% Baptists while late adopters, on average, consisted of 11% Catholics and 19% Baptists.

[24]According to the results from a recent Pew survey (Doherty (2004)), there is a strong relation between political affiliation and liberal versus conservative ideology.

differences within the lowest wealth category (i.e., poor investors), the preference of investors for lottery-type stocks are strongest in African-American dominated regions. Collectively, the evidence indicates that African-Americans are likely to tilt their portfolios most heavily toward lottery-type stocks, followed closely by Hispanics and Whites.

Focusing attention on religious differences, I find that investors who live in states with a greater than average proportion of Protestants (e.g., Minnesota) exhibit weaker preference for lottery-type stocks (see Table V, Panel D). In contrast, investors who live in states with a greater than average proportion of Catholics (e.g., Massachusetts) exhibit stronger preference for lottery-type stocks. Additionally, investors who live in regions with relatively heavier concentration of people without any religious affiliation (e.g., the state of Washington) invest relatively more in stocks with lottery-type features. Overall, the evidence indicates that religion plays a considerable role in shaping investors' attitudes toward gambling in the stock market.

Lastly, I examine whether political affiliation influences gambling behavior in the stock market. When I compare the preferences of investors who reside in counties with Democratic tilt and those who reside in counties with Republican tilt, the differences are ambiguous (see Table V, Panel E).[25] Republicans exhibit preference for stocks with higher idiosyncratic volatility while their skewness preferences are not significantly different from Democrats. The preference differences along mean return and stock price dimensions are also only marginally significant. However, when I condition on wealth, the preference differences become more evident. I find that within the group of poor investors, Republicans exhibit stronger preference (relative to Democrats) for lottery-type stocks. These preference differences are considerably weaker within the group of rich investors. Collectively, the evidence indicates that poor investors who reside in regions dominated by Republicans exhibit stronger preference for stocks with lottery-type features.

E. Does Location Influence Gambling Attitudes?

The location of an individual may influence gambling behavior for several reasons. For instance, a person who lives in an urban area is likely to encounter gambling opportunities more often. Such repeated exposures to gambling opportunities could make her relatively less sensitive to risk (Shiller (2000, pp. 40-42)). Additionally, urban individuals may have higher aspiration levels due to more frequent exposures to affluent people. As a result, urban investors may exhibit relatively stronger gambling tendencies.

To examine whether investors located in urban areas are likely to tilt their portfolios more strongly toward lottery-type stocks, I identify rural and urban investors. I classify

[25] If an investor resides in a county which voted Democrat by a margin of two to one during the 1992 and 1996 presidential elections, I assume that the investor lives in a region dominated by Democrats. Republican regions are identified in an analogous manner.

an investor as an urban investor if she resides within 50 miles of one of the largest twenty metropolitan areas in the U.S. Rural investors are those who reside at least 100 miles away from the center of these twenty metropolitan areas. The remaining investors are classified as suburban investors.[26] Following the panel regression estimation procedure described earlier (see Sections I.C and II.A), I estimate cross-sectional regressions for rural and urban investors.

Table V, Panel F reports the panel regression estimates. I find that rural investors exhibit stronger preference for idiosyncratic volatility while urban investors exhibit relatively stronger preference for skewness. Furthermore, along the price dimension, rural investors exhibit marginally stronger preference for lower-priced stocks. Overall, in these unconditional tests, the preference differences between rural and urban investors are unclear. When I examine the differences in preferences of rural and urban investors after conditioning on wealth, a much clearer picture emerges. I find that relative to poor rural investors, poor urban investors exhibit a significantly stronger preference for lottery-type stocks. However, within the group of rich investors, the differences between rural and urban investors are still ambiguous – rich rural investors exhibit stronger preference for idiosyncratic volatility while rich urban investors exhibit relatively stronger preference for skewness. Collectively, these results indicate that poor urban investors exhibit stronger preference for stocks with lottery-type features.

Collectively, the results from stock-level cross-sectional regressions indicate that investors' preference for lottery-type stocks are influenced by approximately the same set of socio-economic and psychological factors which induce greater lottery participation rates and greater lottery purchases. Overall, people's gambling attitudes revealed in lottery markets appear to spillover into the stock market.

III. A Composite Profile of Stock Market Gamblers

For greater accuracy, I rotate the point-of-view from the cross-section of securities to the cross-section of investors. This alternative perspective provides robustness to my main results but more importantly, it allows me to examine whether the univariate and bivariate test results survive in multivariate settings. Additionally, a multivariate approach allows me to examine the relative strengths of the determinants of stock market gambling behavior identified in the previous section.

[26] For robustness, I checked my results with other distance cutoffs (75 miles, 100 miles) for defining rural and urban investors. My results are robust to these alternative definitions of rural and urban regions.

A. *Measuring Excess Investment in Lottery-Type Stocks*

To generate a composite profile of stock market gamblers, I explicitly define lottery-type stocks where I consider three stock characteristics: idiosyncratic volatility, skewness, and stock price. Motivated by the findings in Section I.B, I assume that stocks in the lowest k^{th} stock price percentile and the highest k^{th} idiosyncratic volatility and skewness percentiles are likely to be perceived as lottery-type stocks. For robustness, I consider two values of k, $k = 33$ and $k = 50$. When $k = 33$, 1,840 stocks are identified as lottery-type stocks and when $k = 50$, there are 3,294 lottery-type stocks in the sample.[27] During the 1991-96 sample-period, a typical lottery-type stock had a market capitalization of \$22 million, a price of \$2.25, a B/M of 0.253, and an institutional ownership of 4.35%.[28] Furthermore, lottery-type stocks are concentrated heavily in energy, mining, bio-technology, and technology sectors.

I measure the excess weight assigned to lottery-type stocks by investor i in month t as:

$$ewls_{it} = \frac{w_{it}^{act} - w_{it}^{exp}}{w_{it}^{exp}}. \tag{2}$$

Here, w_{it}^{act} is the actual weight assigned to lottery-type stocks by investor i in month t. w_{it}^{exp} is the weight of lottery-type stocks in the aggregate market portfolio. The sample-period mean of monthly (i.e., $ewls_i$) provides a measure of an investor's preference for lottery-type stocks.

B. *Multivariate Regression Tests*

To further investigate the nature of individual investors' preferences for lottery-type stocks and to estimate the relative strengths of the various determinants of these preferences, I estimate a regression model where the dependent variable is the sample-period mean excess weight of an investor (i.e., $ewls_i$) in lottery-type stocks. Several variables which characterize household demographics and portfolio characteristics are employed as independent variables. In particular, *Wealth* is the total net worth, *Income* is the total annual household income, and *Age* is the age of the head of the household. The *Retired* dummy is set to one if the head of the household is retired, the *Male Dummy* is set to one if the head of the household is male, the *Married Dummy* is set to one if the head of the household is married, and the *Urban Dummy* is set to one if the household is located in one of the largest twenty metropolitan areas in the U.S.

To examine the relation between over-confidence and investment in lottery-type stocks, I consider an *Overconfidence Dummy* which is set to one for investors who belong to the

[27] The reported results are for $k = 33$ but the results are very similar when I choose $k = 50$. These results are available upon request.

[28] The median values are very similar to the reported means: the median market capitalization, stock price, B/M, and institutional ownership was \$20 million, \$2.02, 0.509, and 3.80%, respectively.

highest portfolio turnover quintile and the lowest risk-adjusted performance quintile. Casual observation suggests that people do not find all types of gambling activities equally attractive. Hunter (1990) finds that games which attract most serious gamblers and those which are most addictive contain a fair mix of chance and skill. Games which contain a small element of skill allow people to modify the final outcome of the gamble. This may give them an illusion of control (Langer (1975)) where they may think they can alter the outcome more than what is actually possible.[29] The stock market, with a fair mix of chance and skill, is likely to be perceived as an attractive setting for gambling. Particularly, people who are over-confident may have a stronger belief that they can out-perform the market and they are likely to exhibit stronger preference for lottery-type stocks.

To capture investors' portfolio and trading characteristics, I include the *Mutual Fund Holdings* variable which measures the proportion of investor's financial portfolio that is allocated to mutual funds. I also consider an *Option Dummy* which is set to one if an investor made at least one trade in an option during the sample-period. Additionally, I consider a number of portfolio characteristics as control variables. This includes the factor exposures of the household portfolio, portfolio's concentration in NASDAQ stocks and 48 Fama-French industries (Fama and French (1997)), portfolio size, and monthly portfolio turnover. For brevity, the coefficient estimates of these control variables are suppressed.[30]

To examine the influence of race/ethnicity, religion, and political influence, I include the *African American-White Ratio* (*Hispanic-White Ratio*) variable which is the ratio of the population of African-Americans (Hispanics) and Whites in an investor's zipcode. The *Catholic Dummy* (*Protestant Dummy*) is set to one if the proportion of Catholics (Protestants) in the state of investor's residence is greater than the mean state-level proportion of Catholics (Protestants) in the U.S. Lastly, *Democratic-Republican Ratio* is the mean ratio of the number of Democratic and Republican votes in an investor's county during the 1992 and 1996 presidential elections.

Table VI reports the cross-sectional regression estimates. Consistent with the univariate and bivariate results (see Tables IV and V), I find that younger, poor, and single men invest disproportionately more in lottery-type stocks. Additionally, investors who reside in rural and Republican dominated areas and belong to one of the minority groups (African-American or Hispanic) exhibit stronger preference for lottery-type stocks. I also find that investors who live in states with greater concentration of Catholics (Protestants) invest more (less) in lottery-type stocks. Finally, I find that investments in lottery-type stocks are higher

[29]Some games do not actually allow people to change the odds of the final payoffs but rather they just provide a false illusion that the outcome can be modified. For instance, when people actually pick numbers in "pick three" games, they feel that they can exert an influence on the final outcome even though the lottery is purely a game of chance. Additionally, not all numbers are perceived to have an equal chance of winning. For instance, in Maryland's three-digit daily game, numbers such as 333 and 777 are almost 40 times more popular than numbers such as 092 and 086 (Clotfelter and Cook (1989)). Also, see Thaler and Ziemba (1988).

[30]These estimated coefficients are available upon request.

for investors who have traded options. Overall, the univariate and bivariate results presented earlier survive in a multivariate setting.

The cross-sectional regression estimates also provide two new results. First, I find that investors who hold larger mutual fund portfolios invest more in lottery-type stocks. This suggests that investors hold a layered portfolio where the lottery-type investments represent the "upside-potential" layer while the relatively less risky mutual fund portfolio represents the "security" layer. These results are consistent with the theoretical predictions of Friedman and Savage (1948) and the behavioral portfolio theory of Shefrin and Statman (2000). Second, I find that investors who are more over-confident (according to my measure) invest disproportionately more in lottery-type stocks.[31] This evidence indicates that behavioral biases are likely to exacerbate investors' preferences for lottery-type stocks.

Comparing the coefficient estimates of the independent variables, I find that investor over-confidence and wealth are the two strongest determinant of investments in lottery-type stocks.[32] An over-confident person invests 23.334% more (relative to the expected investment) in lottery-type stocks. In contrast, an investor whose wealth increases by one standard deviation reduces investments in lottery-type stocks by 22.858%. Age influences gambling behavior in a significant manner too – a one standard deviation increase in age results in 10.361% reduction in investments in lottery-type stocks. Additionally, I find that gender, race/ethnicity, religion, size of mutual fund holdings, and experience with option trading have moderate marginal influence on investors' holdings in lottery-type stocks. And marital status, political affiliation, and location variables have the weakest marginal influence on investors' holdings in lottery-type stocks.

C. Macro-Economic Conditions and Trading in Lottery-Type Stocks

To further understand why certain subsets of individual investors exhibit preference for lottery-type stocks, I focus on investors' trading activities. The trading activities are likely to provide additional insights into the motivation of people who invest disproportionately more in lottery-type stocks. Specifically, I examine whether investors exhibit a greater preference for lottery-type stocks during bad economic times. Lottery studies suggest that when economic opportunities are not very bright, people find the tiny probability of a large gain more attractive and consequently, they exhibit stronger preference for lotteries (Mikesell (1994)). For instance, during the Great Depression of the 1930s, the popularity of

[31] I also experimented with a few other explanatory variables such as the disposition effect (i.e., investor's greater reluctance to realize losses), professional occupation dummy which is set to one if an investor belongs to a professional occupation category, margin account dummy which is set to one if an investor holds a margin account, local bias (i.e., investor's propensity to invest disproportionately more in local stocks), etc. The coefficient estimates for all these variables are statistically insignificant and more importantly, the coefficient estimates for other variables remain virtually unchanged.

[32] The independent variables have been standardized so that the coefficient estimates can be directly compared.

lottery-playing and gambling increased dramatically (Brenner and Brenner (1990, pp. 83-89)). Given a close match between the socio-economic and psychological characteristics of regular lottery-players and stock market lottery-players, it is likely that they respond to variations in economic conditions in a similar fashion.

My sample-period covers the period from January 1991 to November 1996. Around the beginning of the sample-period, the 1990 depression was coming to an end and the economy was starting to expand.[33] During the sample-period, the economy and the stock market grew in a persistent manner. Nevertheless, there was considerable variation in macro-economic conditions during this time period. For instance, the national *unemployment* rate (or *UNEMP*) varied in the range of 5.10-7.80%, the monthly *risk premium* (or *RP*, measured as the difference between the yields of Moody's BAA-rated corporate bond and AAA-rated corporate bond) varied between 1.13% and 2.12%, and the *term spread* (or *TS*, measured as the difference between the yield of a constant-maturity 10-year Treasury bond and the yield of a 3-month Treasury bill) varied between -0.95% and 4.20%. This suggests that if investors' propensity to invest in lottery-type stocks is influenced by macro-economic conditions, it is likely to exhibit a detectable variation even during the relatively short six-year sample-period.

In addition to their sensitivity to macro-economic variables, investors may also be sensitive to changes in the expected future cash-flows of lottery-type stocks.[34] I use revisions in analysts' forecasts of future earnings as proxy for changes in investors' expectations about future cash-flows. Additionally, given their known sensitivity to past returns (e.g., Odean (1999), Dhar and Kumar (2001), Barber and Odean (2005)), investors may respond to recent market or stock returns. With this motivation, I estimate the following time-series regression model to examine the influence of broad economic condition on investors' propensity to buy lottery-type stocks:

$$\begin{aligned} EBSI_t = b_0 &+ b_1 UNEMP_{t-1} + b_2 UEI_{t-1} + b_3 MP_{t-1} + b_4 RP_{t-1} + b_5 TS_{t-1} \\ &+ b_6 EFC_{t-1} + b_7 EFC_t \\ &+ b_8 MKTRET_{t-1} + b_9 MKTRET_t + b_{10} LOTRET_{t-1} + b_{11} LOTRET_t \\ &+ b_{12} EBSI_{t-1} + \epsilon_t. \end{aligned} \tag{3}$$

In the regression specification, I use the $EBSI$ variable to measure the *excess* (relative to non-lottery stocks) change in the sentiment of investors in a given month (i.e., differential sentiment shift). $EBSI$ is defined as, $EBSI_t = LBSI_t - OBSI_t$, where $LBSI_t$ is the buy-sell imbalance (BSI) of lottery stocks in month t and $OBSI_t$ is the buy-sell imbalance of other remaining stocks in month t.[35] Additionally, UEI_t is the unexpected inflation in

[33] According to the NBER, the 1990 recession spanned from July 1990 to March 1991.

[34] If trading in lottery-type stocks is motivated by gambling tendencies, investors may not pay much attention to the fundamentals. Nevertheless, to choose a subset of stocks from the larger set of lottery-type stocks, they *may* consider the fundamentals.

[35] The BSI for portfolio p in month t is defined as, $BSI_{pt} = \frac{100}{N_{pt}} \sum_{i=1}^{N_{pt}} BSI_{it}$ where the BSI for stock i

month t where the average of twelve most recent inflation realizations is used to estimate the expected level of inflation, MP_t is the monthly growth in industrial production, EFC_t is the mean change in analysts' earnings forecasts of lottery-type stocks in month t, $MKTRET_t$ is the monthly market return, and $LOTRET_t$ is the mean monthly return on lottery-type stocks.[36] Lastly, the one-month lagged $EBSI$ variable is used as an explanatory variable which controls for potential auto-correlation in sentiment shifts.

The estimation results are presented in Table VII.[37] I find that higher unemployment rates are associated with positive shifts in differential investor sentiment for lottery-type stocks (coefficient estimate = 1.841, t-stat = 2.008). Put differently, investors buy relatively more (or sell relatively less) lottery-type stocks when macro-economic conditions, as measured by the unemployment rate, are perceived to be poor. This evidence indicates that investors' propensity to buy lottery-type stocks increases during bad economic times. Consistent with this interpretation, I find that differential sentiment shifts are higher when the equity risk premium is higher to compensate for the poor state of the economy (coefficient estimate = 1.139, t-stat = 3.478). The other macro-economic variables I consider are not significantly associated with investors' differential sentiment shifts.

Two additional conclusions can be drawn from the time-series regression estimates. First, the EFC variable which proxies for investors' changing expectations about future cash-flows has insignificant coefficient estimates. This indicates that trading in lottery-type stocks are less likely to be driven by expectations about stock fundamentals. Secondly, I find that differential sentiment shifts are positively associated with contemporaneous returns on lottery-type stocks (coefficient estimate = 3.766, t-stat = 4.043). This suggests that either investors engage in very short-term return-chasing activities or their differential sentiment shifts influence the returns of lottery-type stocks. I examine the sentiment-return relation further in the next section. Collectively, the time-series regression results indicate that investors exhibit similar tendencies in their lottery purchasing and lottery-type stock trading activities – both propensities increase when economic conditions are relatively less favorable.

D. Differential Sentiment Shifts and Stock Returns

If the trading behavior of investors who exhibit a preference for lottery-type stocks contains a systematic component (i.e., if their trades aggregate and do not cancel out), it may influence

in month t is defined as $BSI_{it} = [\sum_{j=1}^{D_t}(VB_{ijt} - VS_{ijt}]/[(\sum_{j=1}^{D_t}(VB_{ijt} + VS_{ijt})]$. Here, D_t is the number of days in month t, VB_{ijt} is the buy volume (measured in dollars) for stock i on day j in month t, VS_{ijt} is the sell volume (measured in dollars) for stock i on day j in month t, and N_{pt} is the number of stocks in portfolio p formed in month t. See Kumar and Lee (2004) for further details.

[36]My choice of macro-economic variables follows Chen, Roll, and Ross (1986) and Ferson and Schadt (1996).

[37]I also experimented with other regression specifications with contemporaneous values of macro-economic variables, lagged unemployment rates measured over a quarter, and innovations in unemployment rates. These results (available upon request) are qualitatively similar to those reported in the paper.

stock returns, especially if arbitrage costs are high. Higher idiosyncratic volatility is one of the defining characteristics of lottery-type stocks and because idiosyncratic volatility has been used as an arbitrage cost proxy for (e.g., Wurgler and Zhuravskaya (2002)), arbitrage costs are likely to be high for lottery-type stocks. Consequently, differential sentiment shifts ($EBSI$) may influence the returns of lottery-type stocks.[38]

To examine the incremental explanatory power of $EBSI$ for returns on lottery-type stocks, I employ a six-factor time-series model which contains the three standard Fama-French factors (Fama and French (1993)), the momentum factor (Jegadeesh and Titman (1993), Carhart (1997)), the liquidity factor (Pástor and Stambaugh (2003)), and the differential sentiment shift ($EBSI$) as explanatory variables. The following multi-factor time-series model is estimated:

$$\begin{aligned} LOTRET_t - R_{ft} &= \alpha + \beta_1 RMRF_t + \beta_2 SMB_t \\ &+ \beta_3 HML_t + \beta_4 UMD_t + \beta_5 LIQ_t + \beta_6 EBSI_t + \varepsilon_t \\ & \qquad t = 1, 2, \ldots, T. \end{aligned} \tag{4}$$

Here, $LOTRET_t$ is the rate of return on the lottery-type stock portfolio, R_{ft} is the riskfree rate of return, $RMRF_t$ is the market return in excess of the riskfree rate, SMB_t is the difference between the value-weighted return of a portfolio of small stocks and the value-weighted return of a portfolio of large stocks, HML_t is the difference between the value-weighted return of a portfolio of high B/M stocks and the value-weighted return of a portfolio of low B/M stocks, UMD_t is the difference between the value-weighted return of a portfolio of stocks with high returns during months $t-12$ to $t-2$ and the value-weighted return of a portfolio of stocks with low returns during months $t-12$ to $t-2$, LIQ_t is the innovation in aggregate liquidity in month t, $EBSI_t$ is the differential sentiment shift in month t, and ε_t is the residual return on the lottery-type stock portfolio.

The estimation results are presented in Table VIII. I find that the $EBSI$ loading is positive (0.104) and statistically significant (t-stat = 2.557). Interestingly, the $EBSI$ variable alone can explain 13.53% of the variation in lottery-type stock returns. The results indicate that $EBSI$ has incremental explanatory power over commonly used risk-factors for lottery-type stock returns. This evidence is consistent with Baker and Wurgler (2005) who find that the subset of stocks which share most attributes with lottery-type stocks are most sensitive to investor sentiment.

For robustness, I estimate the $EBSI$ beta using alternative specifications of the multi-factor model with additional control variables. First, I control for industry exposures, where I follow the Pástor and Stambaugh (2002) methodology and define three industry factors

[38] Because the differential sentiment shift is defined as the difference between the retail sentiment for lottery-type stocks and non-lottery stocks, the market-wide sentiment of retail investors (e.g., Barber, Odean, and Zhu (2003), Kumar and Lee (2004)) cancels out. The measure is similar to the demand-shift differential measure employed in Kumar (2003) for measuring investors' style shifts across extreme style-based portfolios.

which represent the three principal components of the four-factor residuals of the 48 Fama-French industry portfolios. The three industry factors are used as additional controls in a multi-factor model specification. I find that the $EBSI$ beta estimate with industry controls is very similar to the estimate without industry controls ($EBSI$ beta $= 0.101$ with a t-stat of 2.505).

Second, I control for the potential effects of diversification choices of individual investors on lottery-type stock returns. Kumar (2004) finds that a diversification factor which represents returns of a zero-cost portfolio which takes a long (short) position in stocks with the least (most) diversified individual investor clientele has incremental explanatory power (over common risk factors) for a considerable subset of stocks. Furthermore, the sensitivity to the factor is stronger among stocks with lower institutional ownership and higher arbitrage costs. A considerable number of lottery-type stocks have these attributes, so I re-estimate the $EBSI$ beta with controls for industry exposures and under-diversification. Again, I find that the $EBSI$ beta estimate with these controls is very similar to the estimate from the baseline specification without any control variables ($EBSI$ beta $= 0.081$ with a t-stat of 2.250).

Finally, for additional robustness, I use a bivariate vector auto-regression (VAR) framework to examine the nature of the lead-lag relation between the returns on lottery-type stocks (i.e., $LOTRET$) and differential sentiment shifts (i.e., $EBSI$). In particular, I test the null hypothesis that the positive association between $EBSI$ and $LOTRET$ identified previously (see Table VII) indicates that investors engage in short-term trend-chasing and their trading behavior does not influence returns. Stated differently, the null hypothesis posits that the $EBSI$ variable has no ability to predict stock returns. To test this hypothesis, I estimate the following VAR time-series model:

$$\begin{pmatrix} EBSI_t \\ LOTRET_t \end{pmatrix} = \begin{pmatrix} b_{10} \\ b_{20} \end{pmatrix} + \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \begin{pmatrix} EBSI_{t-1} \\ LOTRET_{t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \qquad (5)$$

Table IX presents the VAR estimates and the Granger causality probabilities. The results indicate that there is persistence in $EBSI$ (i.e., $b_{11} > 0$) and also, the one-month lagged returns predict the current $EBSI$ (i.e., $b_{12} > 0$). More importantly, I find that the one-month lagged $EBSI$ has the ability to predict $LOTRET$ (i.e., $b_{21} > 0$). The coefficient $b_{21} = 0.235$ with a t-value of 1.897 and the corresponding Granger probability is 0.062. Overall, the VAR estimates indicate that the null of pure short-term return-chasing can be rejected (p-value < 0.10) – investor trades are influenced by recent returns but their systematic trading also influences the returns of lottery-type stocks.

IV. Lottery-Type Investments and Portfolio Performance

My results so far provide robust evidence of gambling motivated investments by individual investors in the stock market and I also show that systematic trading behavior of investors influences the returns of lottery-type stocks. In this section, I examine whether gambling motivated investment choices influence investors' portfolio performance. It is possible that like the regressive nature of lotteries (e.g., Clotfelter (1979), Clotfelter and Cook (1987), Scott and Garen (1994), Hansen (1995)), the stock market imposes relatively higher costs on under-privileged investors who may be trying to escape poverty using their stock investments. Specifically, I examine whether investor portfolios under-perform the typical benchmarks and whether portfolio under-performance varies cross-sectionally across different investor groups.[39]

A. *Univariate Tests: Gambling Intensity and Portfolio Performance*

To examine the impact of investors' gambling tendencies on portfolio performance, first, I compare the mean performance levels of investors who invest in lottery-type stocks (i.e., "gamblers") with those who do not hold lottery-type stocks even once during the sample-period (i.e., "non-gamblers"). Lottery-type stocks are identified following the description of lottery-stocks outlined in Section III.A. I examine both raw and risk-adjusted performance differentials between the two broad investor categories.

The performance results are reported in Table X, Panel A. I find that the mean raw annual performance differential between the two groups is economically small (only 0.468%). However, the mean four-factor alpha of gamblers is considerably higher than the mean four-factor alpha of non-gamblers (-0.637 for gamblers versus -0.148 for non-gamblers). The difference is statistically significant (p-value < 0.01) and translates into an economically significant annual risk-adjusted performance differential of 5.868%. The mean factor exposures provide some insights into the determinants of these performance differentials – the portfolios of gamblers are tilted heavily toward small-cap and value stocks.

Next, to estimate the impact of gambling intensity on portfolio performance, I sort the portfolios of gamblers into ten groups based on the weights they assign to lottery-type stocks. These results are also presented in Table X (see Panel B). The results indicate that both raw and risk-adjusted performance measures paint a consistent picture – the performance declines in an almost monotonic fashion as the weight assigned to lottery-type stocks increases. For "mild gamblers" (decile 1), the mean monthly return is 1.432% while the mean four-factor alpha is -0.176. In contrast, for "heavy gamblers" (decile 10), the mean monthly

[39]As discussed in detail in footnote 9, investors who invest in lottery-type stocks may not necessarily be acting in an irrational manner even when their portfolios under-perform the typical passive performance benchmarks. Without an accurate specification of their preference structure, inferences about rationality cannot be drawn unambiguously. Such an analysis would be quite interesting but it is beyond the focus and the scope of my paper.

return is 0.684% while the mean four-factor alpha is −1.273. This translates into an economically significant annual raw performance differential of −8.976% and an annual risk-adjusted performance differential of −13.164%. Overall, the performance estimates reveal that stock market gamblers are paying significant costs for their gambling motivated investment choices.

B. *Bivariate Tests: Portfolio Under-Performance Estimates within Income Categories*

To better interpret the portfolio under-performance, I compare the portfolio performance of gamblers and non-gamblers within each of the nine income categories. The results are presented in Table XI. I find that within the group of gamblers (Panel A) as well as non-gamblers (Panel B), the mean four-factor alpha increases with income (but still stays negative) while the variation along the mean return measure is more uneven. I also find that the proportion of investors who are gamblers within a given income group decreases with income. For instance, 23.62% of investors who earn less than $15,000 annually gamble (i.e., invest in lottery-type stocks), while in the high-income category (annual income > $125,000), 18.38% of investors gamble. Consistent with the results reported previously, this evidence indicates that gambling tendency decreases with income.

More importantly, I find that, within each income category, gamblers under-perform non-gamblers. For instance, the mean four-factor alpha for gamblers in the highest income group is −0.779 but the corresponding measure for non-gamblers is considerably lower (−0.190). This monthly difference translates into an economically significant annual risk-adjusted performance differential of 7.068%. The gambler-non-gambler performance differential is most severe in the lowest income category (annual income < $15,000). Within this income group, the mean four-factor alpha for gamblers is −1.104, the mean four-factor alpha for non-gamblers is −0.337, and this monthly difference translates into an economically significant annual risk-adjusted performance differential of 9.204%.

I also examine portfolio under-performance in dollar terms. I find that among gamblers (Panel A), the mean under-performance is high for the extreme income categories and it varies unevenly with income. Importantly, these under-performance measures are significant proportions of investors' annual income. For instance, the annual risk-adjusted under-performance is 5.28% of the annual income of investors whose annual income ranges between $50,000 and $75,000.[40] The annual under-performance is almost 32% of annual income for investors who are in the lowest income group (annual income < $15,000). The annual under-performance is a significant proportion of annual income even among investors who do not invest in lottery-type stocks (see Panel B) but those proportions are significantly lower than the mean under-performance proportions for gamblers.

To examine the portfolio under-performance within the group of gamblers as gambling

[40] I use the upper limit of the income range to obtain these relative under-performance measures. So, the estimates represent a lower bound on under-performance.

intensity varies, I divide gamblers into three categories based on their portfolio weight in lottery-type stocks. Investors whose portfolio weights are in deciles 1-3, 4-7, and 8-10 are identified as low, medium, and high intensity gamblers, respectively. I compute the annual risk-adjusted under-performance as a proportion of annual income for each of these three groups of investors within each income category. The results are presented in Figure 1. As expected, I find that, within most income groups, the portfolio under-performance is greater for high intensity gamblers. For instance, within the lowest income category, the annual relative under-performance for high and low intensity gamblers are -34.72% and -8.65%, respectively. Overall, these results indicate that investors with gambling mindset under-perform the typical performance benchmarks, where the degree of under-performance is greater among high intensity gamblers.

C. Isolating the Effects of Gambling Intensity on Portfolio Performance

Investors who exhibit preference for lottery-type stocks may also have other characteristics which may reduce their portfolio performance. For instance, those investors may exhibit stronger behavioral biases such as the disposition effect (e.g., Shefrin and Statman (1985), Odean (1998)) or the familiarity bias (e.g., Huberman (2001), Grinblatt and Keloharju (2001), Zhu (2002), Ivković and Weisbenner (2005)). To isolate the impact of investors' preferences for lottery-type stocks on portfolio performance, I examine the relation between the *residual* risk-adjusted portfolio performance and weight assigned to lottery-type stocks. The residual performance measure is the residual from a cross-sectional regression where the risk-adjusted portfolio performance is the dependent variable and the set of explanatory variables includes investor's age, income, wealth, portfolio size, portfolio monthly turnover, portfolio diversification, familiarity (or local) bias measure, and the adjusted disposition effect measure.[41]

Using the residual performance measure, I find that the mean four-factor alpha differential between "mild gamblers" and "heavy gamblers" is still high ($= -0.805$). This translates into an annual risk-adjusted performance differential of -9.660%. Additionally, I find that a one standard deviation shift in the weight assigned to lottery-type stocks corresponds to an additional annual risk-adjusted under-performance of 3.276%. Collectively, the results indicate that portfolios of investors who invest disproportionately more in lottery-type stocks

[41]The portfolio diversification is measured as the negative of the normalized portfolio variance (see Goetzmann and Kumar (2004)). The local bias of an investor is defined as, $LB = D_{act} - D_{mkt}$, where D_{act} is the distance between an investor's location and her stock portfolio and D_{mkt} is the distance between an investor's location and the market portfolio. See Coval and Moskowitz (2001) and Zhu (2002) for details of the local bias measure. Note that the results are qualitatively similar when I use other related measures of local bias (e.g., the proportion of portfolio that is invested in firms located within a 100 or 250 mile radius from an investor's location). The adjusted disposition effect measure for an investor is defined as the difference between an investor's actual propensity to realize gains and the expected propensity to realize gains, relative to her portfolio size and trading frequency matched peer group. See Kumar and Lim (2004) for details of the adjusted disposition effect measure.

exhibit significant under-performance, even when I control for the effects of other known determinants of portfolio performance.

D. Robustness Checks

I do not have income information for 20,951 (about 38%) investors. To assure that a sample selection bias is not contaminating my results, I obtain the performance measures for investors without income data and compare the under-performance of gamblers and non-gamblers. For investors with missing income data, I find that gamblers have a mean four-factor alpha of -0.807 while non-gamblers have a mean four-factor alpha of -0.230. In contrast, for investors with income data, lottery-players have a mean four-factor alpha of -0.805 while non-lottery-players have a mean four-factor alpha of -0.255. The corresponding performance differences are statistically insignificant. This evidence indicates that the mean under-performance of investors with missing income data is very similar to the mean under-performance of investors with income data. Overall, these comparisons indicate that my under-performance estimates are robust to concerns about a potential sample selection bias due to missing income data.

In sum, the performance comparisons indicate that the stock market and lotteries markets are equally unsympathetic to under-privileged people. Those people pay relatively greater proportions of their income as indirect taxes when they purchase lottery tickets and they lose relatively greater proportions of their income in the stock market.[42] While under-privileged individuals might view lotteries and stock investments as their only means to escape poverty, in reality, they are probably digging deeper holes for themselves.

V. Summary and Conclusion

This paper examines whether socio-economic and psychological factors which are known to influence lottery purchases lead to excess investment in lottery-type stocks. Using monthly portfolio holdings and trading data from a large U.S. brokerage house, I find that, individual investors invest disproportionately more in stocks with higher idiosyncratic volatility, higher skewness, and lower prices even though these stocks have lower mean returns. These preferences are distinct from individual investors' known preferences for certain firm characteristics such as small-cap stocks, value stocks, etc. In contrast, institutional investors prefer stocks

[42] My paper is certainly not the first one to provide strong evidence of under-performance in individual investor portfolios. Several previous studies have investigated the performance of individual investors considered in this paper. Barber and Odean (2000) show that there is rich cross-sectional variation in the performance of individual investors. Other related studies (e.g., Coval, Hirshleifer, and Shumway (2001), Ivković, Poterba, and Weisbenner (2004), Ivković, Sialm, and Weisbenner (2004)) have identified the profile of investors in the right tail of the performance distribution. My results provide an additional glimpse into the profile of investors who lie in the left tail of the performance distribution.

with higher mean returns, lower idiosyncratic volatility, lower skewness, and higher prices. Furthermore, individual investors' demand for lottery-type stocks increases when economic conditions are poor and those demand shifts influence the returns of lottery-type stocks.

Examining cross-sectional differences within the individual investor category, I find that socio-economic and psychological factors which induce higher expenditures in lotteries also induce greater investment in lottery-type stocks – poor, young men who live in urban, Republican dominated regions and belong to specific minority (African-American and Hispanic) and religious (Catholic) groups invest more in stocks with lottery-type features. Collectively, these results indicate that people's attitudes toward gambling are reflected in their stock investment decisions. The finding that race, religion, and political ideology influence portfolio choices of investors is not surprising, but so far, this idea has not been imported in the portfolio choice literature.

Examining the portfolio performance of investors who invest in lottery-type stocks, I find that the annual under-performance is roughly 5% of investors' annual household income, where the range is 2-32%. Investors in the lowest income group (annual income $<$ \$15,000) have a mean annual under-performance of \$4,725 which is almost 32% of their annual income. High-income investors also have comparable mean annual under-performance (\$4,250) but it is only 1.70% of their annual income. Taken together, my results indicate that investors who are pre-disposed to playing lotteries also exhibit strong preferences for lottery-type stocks in their investment choices. More importantly, and sadly, poor investors, who can least afford to under-perform, incur the largest costs for their gambling motivated investments.

Collectively, the evidence in the paper indicates that people's attitudes toward gambling are reflected in their stock investment choices and stock returns. And broadly speaking, my results suggest that due to our fundamental desire to gamble, the link between socio-economic dynamics and the stock market behavior may be stronger than currently believed. Of course, this should not come as a surprise as psychological, social, economic, religious, and political identities of an individual supersede her identity as an investor.

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Table I

Individual versus Institutional Investors: Actual and Expected Weights in Price and Moment-Based Stock Categories

This table reports the actual and expected weights assigned to sixteen stock categories in the aggregate individual and institutional investor portfolios. I divide all stocks in the sample into sixteen categories using independent sorts along mean return, idiosyncratic volatility, skewness, and stock price dimensions. Stocks are assigned to the upper or the lower half along each of these four dimensions, and sixteen stock categories are obtained. The return moments are calculated using past 60 months of data and the stock price measure is the average price during the sample-period. The idiosyncratic volatility measure is the variance of the residual obtained by fitting a four-factor model to the monthly stock returns series over the past 60 months. The expected weights in stock categories reflect the weight of the stock category in the aggregate market portfolio where the market portfolio is obtained by combining all CRSP stocks. The averages of the 71 monthly actual and expected weights are reported in the table. The individual investor data are from a large U.S. discount brokerage house for the 1991-96 time-period. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Individual Investors				Institutional Investors			
Stock Category	Actual	Expected	Diff	Diff (%)	Actual	Expected	Diff	Diff (%)
High Volatility, High Skew								
Low Price, Low Ret	8.33	0.74	7.59***	1030.88	0.28	0.74	−0.46***	−61.64
High Price, Low Ret	0.60	0.23	0.37***	165.68	0.19	0.23	−0.04*	−17.62
Low Price, High Ret	9.09	1.05	8.04***	768.90	0.36	1.05	−0.69***	−65.25
High Price, High Ret	5.65	2.48	3.17***	127.45	2.53	2.48	0.05	2.00
High Volatility, Low Skew								
Low Price, Low Ret	2.50	0.38	2.12***	557.95	0.25	0.38	−0.13*	−35.06
High Price, Low Ret	0.99	0.34	0.65***	195.65	0.35	0.34	0.01	3.81
Low Price, High Ret	1.32	0.21	1.11***	520.17	0.14	0.21	−0.07**	−36.07
High Price, High Ret	6.82	3.50	3.32***	94.81	4.75	3.50	1.25***	35.71
Low Volatility, High Skew								
Low Price, Low Ret	1.37	0.46	0.91***	196.88	0.24	0.46	−0.22***	−48.46
High Price, Low Ret	2.52	2.91	−0.39***	−13.30	2.27	2.91	−0.64***	−22.03
Low Price, High Ret	0.36	0.12	0.24***	198.88	0.05	0.12	−0.07***	−59.25
High Price, High Ret	5.04	8.29	−3.25***	−39.12	8.40	8.29	0.11*	1.38
Low Volatility, Low Skew								
Low Price, Low Ret	1.66	1.57	0.09*	5.84	0.31	1.57	−1.26***	−79.96
High Price, Low Ret	20.21	23.61	−3.40***	−14.42	22.02	23.61	−1.59***	−6.74
Low Price, High Ret	0.24	0.16	0.08**	46.67	0.06	0.16	−0.10***	−63.68
High Price, High Ret	33.27	53.94	−20.67***	−38.33	57.79	53.94	3.85***	7.14

Table II
Panel Regression Estimates for Aggregate Individual and Institutional Portfolios

This table reports the panel regression estimates for cross-sectional regressions where the excess weight assigned to a stock in the aggregate individual or institutional portfolio is the dependent variable. The excess portfolio weight allocated to stock i in month t is given by: $EW_{ipt} = \frac{w_{ipt} - w_{imt}}{w_{imt}} \times 100$, where, w_{ipt} is the actual weight assigned to stock i in group portfolio p in month t and w_{imt} is the weight of stock i in the aggregate market portfolio in month t. The mean return, idiosyncratic volatility, skewness, kurtosis, and the price of the stock is used as independent variables. Additionally, the following control variables are employed: (i) market beta, which is estimated using past 60 months of data, (ii) firm size, (iii) book-to-market ratio, (iv) short-term momentum (past one-month stock return), (v) longer-term momentum (past twelve-month stock return), and (vi) an S&P500 dummy which is set to one if the stock belongs to the S&P500 index. The t-statistic for the coefficient estimate is reported in parenthesis below the estimate. The individual investor data are from a large U.S. discount brokerage house for the 1991-96 time-period while the institutional holdings data are from Thomson Financial.

Dependent variable: Excess portfolio weight (in percent) in stock i in the aggregate portfolio.

	Individuals			Institutions
Variable	(1)	(2)	(3)	(4)
Mean Return	−1.305		−0.955	1.360
	(−42.856)		(−24.429)	(40.455)
Idiosyncratic Volatility	1.234		0.905	−0.258
	(47.011)		(33.141)	(−19.931)
Skewness	0.581		0.408	−0.106
	(43.153)		(29.866)	(−7.635)
Kurtosis	−0.676		−0.580	−0.047
	(−39.018)		(−33.081)	(−3.928)
Stock Price	−0.437		−0.201	0.290
	(−32.089)		(−23.694)	(21.837)
Market Beta		0.055	0.055	0.382
		(1.126)	(0.647)	(32.212)
Log(Firm Size)		−0.969	−0.683	0.270
		(−41.153)	(−35.416)	(21.025)
Book-To-Market Ratio		−0.275	−0.285	−0.048
		(−21.525)	(−19.611)	(−8.845)
Past 1-month Stock Return		0.016	0.038	−0.047
		(1.834)	(2.548)	(−5.608)
Past 12-month Stock Return		−0.050	−0.023	0.007
		(−4.833)	(−1.163)	(0.570)
S&P 500 Dummy		0.076	0.060	−0.047
		(21.068)	(13.775)	(−8.728)
Month/Quarter Fixed Effects	Yes	Yes	Yes	Yes
Number of Observations	155,725	206,977	141,043	59,238
Adjusted R^2	10.58%	7.52%	13.64%	21.03%

Table III

Wealth-Sorted Investor Groups: Actual and Expected Weights in Price and Moment-Based Stock Categories

This table reports the actual and expected weights assigned to sixteen stock categories in the aggregate portfolios of poor (wealth deciles 1-3), moderately wealthy (wealth deciles 4-7), and rich (wealth deciles 8-10). Investors in the "poor" category have total net worth of $75,000 or below while investors in the "rich" category have total net worth of $200,000 and above. I divide all stocks in the sample into sixteen categories using independent sorts along mean return, idiosycratic volatility, skewness, and stock price dimensions. Stocks are assigned to the upper or the lower half along each of these four dimensions, and sixteen stock categories are obtained. The return moments are calculated using past 60 months of data and the stock price measure is the average price during the sample-period. The idiosyncratic volatility measure is the variance of the residual obtained by fitting a four-factor model to the monthly stock returns series over the past 60 months. The averages of the 71 monthly actual and expected weights are reported in the table. The individual investor data are from a large U.S. discount brokerage house for the 1991-96 time-period. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Stock Category	Poor	D4-D7	Rich	Poor−Rich	Diff (%)
High Volatility, High Skew					
Low Price, Low Ret	8.67	8.64	7.69	0.98***	12.81
High Price, Low Ret	0.66	0.60	0.56	0.10***	17.55
Low Price, High Ret	9.67	9.31	8.29	1.38***	16.64
High Price, High Ret	5.69	5.76	5.50	0.19**	3.42
High Volatility, Low Skew					
Low Price, Low Ret	2.56	2.53	2.42	0.14**	6.12
High Price, Low Ret	1.20	0.92	0.86	0.34***	40.10
Low Price, High Ret	1.52	1.22	1.21	0.31***	25.43
High Price, High Ret	7.03	6.82	6.62	0.41**	6.25
Low Volatility, High Skew					
Low Price, Low Ret	1.31	1.39	1.42	−0.11**	−7.44
High Price, Low Ret	2.47	2.41	2.70	−0.23**	−8.55
Low Price, High Ret	0.36	0.33	0.38	−0.02	−5.96
High Price, High Ret	4.98	4.89	5.26	−0.28**	−5.31
Low Volatility, Low Skew					
Low Price, Low Ret	1.64	1.70	1.65	−0.01	−0.41
High Price, Low Ret	19.68	19.90	21.05	−1.37**	−6.52
Low Price, High Ret	0.21	0.26	0.26	−0.05*	−20.67
High Price, High Ret	32.35	33.31	34.14	−1.79**	−5.25

Table IV

Panel Regression Estimates for Wealth-Based Group Portfolios

This table reports the panel regression estimates for cross-sectional regressions where the excess weight assigned to a stock in the aggregate portfolio is the dependent variable. Three aggregate portfolios are considered: the aggregate portfolio of the poor (wealth deciles 1-3), moderately wealthy (wealth deciles 4-7), and rich (wealth deciles 8-10). Investors in the "poor" category have total net worth of \$75,000 or below while investors in the "rich" category have total net worth of \$200,000 and above. The excess portfolio weight allocated to stock i in month t is given by: $EW_{ipt} = \frac{w_{ipt} - w_{imt}}{w_{imt}} \times 100$, where, w_{ipt} is the actual weight assigned to stock i in group portfolio p in month t and w_{imt} is the weight of stock i in the aggregate market portfolio in month t. The mean return, idiosyncratic volatility, skewness, kurtosis, and the price of the stock is used as independent variables. Additionally, the following control variables are employed: (i) market beta, which is estimated using past 60 months of data, (ii) firm size, (iii) book-to-market ratio, (iv) short-term momentum (past one-month stock return), (v) longer-term momentum (past twelve-month stock return), and (vi) an S&P500 dummy which is set to one if the stock belongs to the S&P500 index. The t-statistic for the coefficient estimate is reported in parenthesis below the estimate. The individual investor data are from a large U.S. discount brokerage house for the 1991-96 time-period.

Dependent variable: Excess portfolio weight (in percent) in stock i in the group-level portfolio.

	Wealth Deciles			
Variable	D1-D3 (Poor)	D4-D7	D8-D10 (Rich)	Poor−Rich
Mean Return	−1.441	−0.903	−0.479	−0.994
	(−21.241)	(−12.644)	(−19.049)	(−14.503)
Idiosyncratic Volatility	1.704	0.630	0.422	1.275
	(31.131)	(18.891)	(20.296)	(24.048)
Skewness	0.477	0.277	0.281	0.200
	(21.908)	(25.880)	(18.766)	(8.597)
Kurtosis	−0.754	−0.562	−0.365	−0.389
	(−25.071)	(−23.886)	(−20.319)	(−12.436)
Stock Price	−0.241	−0.244	−0.168	−0.082
	(−13.339)	(−10.275)	(−24.061)	(−5.786)
Market Beta	0.083	0.043	0.047	−0.029
	(2.160)	(1.212)	(1.035)	(−1.052)
Log(Firm Size)	−0.761	−0.555	−0.232	−0.511
	(−18.365)	(−13.955)	(−19.846)	(−8.079)
Book-To-Market Ratio	−0.522	−0.145	−0.151	−0.359
	(−21.775)	(−7.571)	(−10.676)	(−14.685)
Past 1-month Stock Return	0.050	0.044	0.010	0.037
	(1.900)	(2.173)	(0.657)	(1.336)
Past 12-month Stock Return	−0.177	0.006	−0.008	−0.155
	(−4.836)	(−0.572)	(0.215)	(−4.068)
S&P500 Dummy	0.027	0.077	−0.020	0.044
	(3.828)	(14.385)	(−4.390)	(6.182)
Month Fixed Effects	Yes	Yes	Yes	Yes
Number of Obervations	141,043	141,043	141,043	141,043
Adjusted R^2	9.43%	7.91%	5.29%	2.56%

Table V
Panel Regression Estimates for Portfolios of Individual Investor Demographic Groups

This table reports the panel regression estimates for cross-sectional regressions where the excess weight assigned to a stock in the aggregate portfolio is the dependent variable. Several aggregate portfolios are considered. Panels A-F report the results for the following sets of group portfolios: (i) Panel A: age and wealth sorted portfolios, (ii) Panel B: gender and marital status based portfolios, (iii) Panel C: race/ethnicity and wealth sorted portfolios, (iv) Panel D: religious affiliation based portfolios, (v) Panel E: political affiliation and wealth based portfolios, and (vi) Panel F: location and wealth sorted portfolios. Investors in the "poor" category have total net worth of $75,000 or below while investors in the "rich" category have total net worth of $200,000 and above. The three age categories are younger (age below 40), middle-aged (age between 40 and 65), and older (age above 65). The excess portfolio weight allocated to stock i in month t is given by: $EW_{ipt} = \frac{w_{ipt} - w_{imt}}{w_{imt}} \times 100$, where, w_{ipt} is the actual weight assigned to stock i in group portfolio p in month t and w_{imt} is the weight of stock i in the aggregate market portfolio in month t. The mean return, idiosyncratic volatility, skewness, kurtosis, and the price of the stock is used as independent variables. Additionally, the following control variables are employed: (i) market beta, which is estimated using past 60 months of data, (ii) firm size, (iii) book-to-market ratio, (iv) short-term momentum (past one-month stock return), (v) longer-term momentum (past twelve-month stock return), and (vi) an S&P500 dummy which is set to one if the stock belongs to the S&P500 index. The retail investor data are from a large U.S. discount brokerage house for the 1991-96 time-period, the zipcode-level race/ehtnicity data are from the 1990 U.S. Census, the state-level religious denomination data are from the 2001 American Religious Identification Survey, and county-level political affiliation data are from the 1992 and the 1996 presidential elections. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Panel Regression Estimates for Age Based Investor Groups

Investor Group	Mean Return	Volatility	Skewness	Kurtosis	Stock Price
Younger	−0.938***	1.031***	0.400***	−0.468***	−0.254***
Middle-Aged	−1.034***	0.982***	0.445***	−0.640***	−0.192***
Older	−0.661***	0.571***	0.161***	−0.215***	−0.201***
Young − Old	−0.221***	0.415***	0.240***	−0.274***	−0.047***
Poor and Younger	−1.201***	0.968***	0.283***	−0.500***	−0.357***
Poor and Middle-Aged	−1.651***	1.358***	0.531***	−0.642***	−0.270***
Poor and Older	−0.152**	0.431***	0.307***	−0.222***	−0.198***

Panel B: Panel Regression Estimates for Gender and Marital Status Based Investor Groups

Investor Group	Mean Return	Volatility	Skewness	Kurtosis	Stock Price
Men	−0.826***	0.836***	0.467***	−0.533***	−0.200***
Women	−0.893***	0.657***	0.153***	−0.312***	−0.186***
Men − Women	0.058*	0.183***	0.307***	−0.229***	−0.020**
Single	−1.003***	0.948***	0.536***	−0.391***	−0.171***
Married	−0.721***	0.667***	0.373***	−0.463***	−0.201***
Single − Married	−0.268***	0.264***	0.133***	0.074***	0.025**
Single Men	−0.998***	1.093***	0.574***	−0.496***	−0.183***
Single Women	−0.779***	0.573***	0.001	−0.113***	−0.153***

Table V(Continued)

Panel Regression Estimates for Portfolios of Individual Investor Demographic Groups

Panel C: Panel Regression Estimates for Race and Ethnicity Based Investor Groups

Investor Group	Mean Return	Volatility	Skewness	Kurtosis	Stock Price
African American	−1.110***	1.176***	0.427***	−0.619***	−0.146***
Hispanic	−1.128***	1.050***	0.360***	−0.537***	−0.216***
White	−0.822***	0.871***	0.218***	−0.432***	−0.240***
Afr Am − White	−0.322***	0.324***	0.216***	−0.092**	−0.093***
Afr Am − Hispanic	−0.064**	0.160***	0.067***	−0.073***	0.046***
Poor African American	−2.025***	1.828***	0.570***	−0.580***	−0.366***
Poor Hispanic	−1.567***	1.279***	0.396***	−0.563***	−0.314***
Poor White	−0.795***	0.836***	0.410***	−0.442***	−0.248***

Panel D: Panel Regression Estimates for Religion Based Investor Groups

Investor Group	Mean Return	Volatility	Skewness	Kurtosis	Stock Price
Catholic	−0.949***	0.876***	0.336***	−0.450***	−0.163***
No Religion	−0.884***	0.934***	0.313***	−0.480***	−0.198***
Protestant	−0.534***	0.306***	0.114***	−0.182***	−0.178***
Catholic − Protestant	−0.302***	0.512***	0.187***	−0.219***	−0.012

Panel E: Panel Regression Estimates for Political Affiliation Based Investor Groups

Investor Group	Mean Return	Volatility	Skewness	Kurtosis	Stock Price
Republican	−0.715***	1.021***	0.260***	−0.531***	−0.166***
Democrat	−0.854***	0.603***	0.284***	−0.386***	−0.184***
Republican − Democrat	0.066*	0.443***	−0.010	−0.156***	0.022*
Poor Republican	−1.491***	1.216***	0.425***	−0.572***	−0.341***
Poor Democrat	−0.589***	0.576***	0.231***	−0.441***	−0.239***
Poor Republican − Poor Democrat	−0.973***	0.689***	0.211**	−0.175**	−0.116***
Rich Republican	−0.338***	0.256***	0.088***	−0.156***	−0.099***
Rich Democrat	−0.203***	0.252***	−0.030**	−0.043**	−0.065***
Rich Republican − Poor Democrat	−0.113**	0.007	0.102***	−0.102***	−0.023*

Panel F: Panel Regression Estimates for Location Based Investor Groups

Investor Group	Mean Return	Volatility	Skewness	Kurtosis	Stock Price
Urban	−0.963***	0.758***	0.392***	−0.503***	−0.185***
Suburban	−0.951***	0.873***	0.304***	−0.393***	−0.212***
Rural	−0.685***	0.939***	0.227***	−0.441***	−0.209***
Urban − Rural	−0.250***	−0.184***	0.163***	−0.047**	0.021*
Poor Urban	−1.569***	1.738***	0.402***	−0.524***	−0.345***
Poor Rural	−0.985***	0.807***	0.360***	−0.440***	−0.216***
Poor Urban − Poor Rural	−0.551***	0.928***	0.043**	−0.066**	−0.127***
Rich Urban	−0.305***	0.232***	0.175***	−0.262***	−0.118***
Rich Rural	−0.453***	0.566***	−0.032*	−0.125***	−0.211***
Rich Urban − Poor Rural	0.164***	−0.349***	0.206***	−0.131***	0.094***

Table VI

Investor Characteristics and Excess Investment in Lottery-Type Stocks

This table reports the estimates of cross-sectional regressions. The dependent variable is the excess stock holding of an investor in lottery-type stocks. Among the independent variables, *Wealth* is the total net worth, *Income* is the total annual household income, and *Age* is the age of the head of the household. The *Retired* dummy is set to one if the head of the household is retired, the *Male Dummy* is set to one if the head of the household is male, the *Married Dummy* is set to one if the head of the household is married, and the *Urban Dummy* is set to one if the household is located in one of the largest twenty metropolitan areas in the U.S. The *Overconfidence Dummy* is set to one for investors who belong to the highest portfolio turnover quintile and the lowest risk-adjusted performance quintile. The *Mutual Fund Holdings* variable measures the proportion of investor's financial portfolio that is allocated to mutual funds. The *Option Dummy* is set to one if an investor made at least one trade in an option during the sample-period. The *African American-White Ratio* (*Hispanic-White Ratio*) variable is the ratio of the population of African-Americans (Hispanics) and Whites in investor's zipcode. The *Catholic Dummy* (*Protestant Dummy*) is set to one if the proportion of Catholics (Protestants) in the state of investor's residence is greater than the mean proportion of Catholics (Protestants) across the U.S. The *Democratic-Republican Ratio* is the ratio of the number of Democratic and Republican votes in investor's county during the 1992 and 1996 presidential elections. The t-statistic for the coefficient estimate is reported in parenthesis below the estimate. The retail investor data are from a large U.S. discount brokerage house for the 1991-96 time-period, the zipcode-level race/ethnicity data are from the 1990 U.S. Census, the state-level religious denomination data are from the 2001 American Religious Identification Survey, and county-level political affiliation data are from the 1992 and the 1996 presidential elections.

Dependent variable: Excess investment (in percent) of an investor in lottery-type stocks.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Constant	24.613	24.409	25.223	25.336	24.571	25.697
	(25.141)	(18.294)	(17.821)	(17.844)	(14.001)	(12.698)
Wealth	−22.141	−19.726	−21.908	−21.918	−25.036	−22.858
	(−11.750)	(−7.185)	(−8.719)	(−8.746)	(−6.163)	(−6.027)
Income	−4.813	−8.411	−8.033	−8.146	−6.577	−6.794
	(−2.245)	(−2.935)	(−2.643)	(−2.691)	(−1.456)	(−1.592)
Age		−7.833	−7.808	−7.591	−10.904	−10.361
		(−2.279)	(−2.188)	(−2.125)	(−2.053)	(−2.056)
Retired Dummy		−7.672	−8.156	−8.087	−5.726	−5.132
		(−2.338)	(−2.405)	(−2.381)	(−2.155)	(−2.093)
Male Dummy			10.489	10.631	6.083	7.147
			(3.053)	(3.089)	(3.137)	(2.431)
Married Dummy			−1.073	−1.134	−0.866	−1.345
			(−2.311)	(−2.328)	(−2.137)	(−2.056)
Urban Dummy				2.911	2.051	2.148
				(2.875)	(2.457)	(3.035)
Over-Confidence Dummy				20.823	20.166	23.334
				(6.115)	(4.396)	(5.139)
Mutual Fund Holdings					6.940	5.703
					(3.485)	(3.387)
Option Dummy					12.851	12.573
					(2.592)	(2.488)
African American-White Ratio						6.483
						(5.139)
Hispanic-White Ratio						5.524
						(2.513)
Catholic Dummy						7.361
						(2.698)
Protestant Dummy						−6.228
						(−2.148)
Democratic-Republican Ratio						−3.380
						(−2.805)
Number of Observations	15,380	10,653	10,274	10,274	10,274	10,274
Adjusted R^2	0.94%	1.30%	1.74%	2.73%	3.35%	4.86%

Table VII
Macro-Economic Conditions and Lottery-Stock Sentiment Shifts

This table reports the estimation results for the following time-series regression model:

$$\begin{aligned}EBSI_t = b_0 &+ b_1 UNEMP_{t-1} + b_2 UEI_{t-1} + b_3 MP_{t-1} + b_4 \Delta RP_{t-1} + b_5 \Delta TS_{t-1} \\ &+ b_6 EFC_{t-1} + b_7 EFC_t \\ &+ b_8 MKTRET_{t-1} + b_9 MKTRET_t + b_{10} LOTRET_{t-1} + b_{11} LOTRET_t \\ &+ b_{12} EBSI_{t-1} + \epsilon_t.\end{aligned}$$

The $EBSI$ variable measures the *excess* change in the sentiment of investors in a given month. $EBSI$ is defined as, $EBSI_t = LBSI_t - OBSI_t$, where $LBSI_t$ is the buy-sell imbalance (BSI) of lottery stocks in month t and $OBSI_t$ is the buy-sell imbalance of other remaining stocks in month t. The BSI for portfolio p in month t is defined as, $BSI_{pt} = \frac{100}{N_{pt}} \sum_{i=1}^{N_{pt}} BSI_{it}$ where the BSI for stock i in month t is defined as $BSI_{it} = [\sum_{j=1}^{D_t}(VB_{ijt} - VS_{ijt}]/[(\sum_{j=1}^{D_t}(VB_{ijt} + VS_{ijt})]$. D_t is the number of days in month t, VB_{ijt} is the buy volume (measured in dollars) for stock i on day j in month t, VS_{ijt} is the sell volume (measured in dollars) for stock i on day j in month t, and N_{pt} is the number of stocks in portfolio p formed in month t. Additionally, UEI_t is the unexpected inflation in month t where the average of twelve most recent inflation realizations is used to estimate the expected level of inflation, MP_t is the monthly growth in industrial production, EFC_t is the mean change in analysts' earnings forecasts of lottery-type stocks in month t, $MKTRET_t$ is the monthly market return, and $LOTRET_t$ is the mean monthly return on lottery-type stocks. To allow for direct comparison among the coefficient estimates, variables are standardized so that each variable has a mean of 0 and a standard deviation of 1. The Newey-West adjusted t-values of the coefficient estimates are reported. The retail investor data are from a large U.S. discount brokerage house for the 1991-96 time-period.

Dependent variable: Aggregate monthly excess buy-sell imbalance (EBSI) for lottery-type stocks.

	(1)		(2)		(3)		(4)		(5)	
Variable	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Intercept	6.012	5.599	6.585	6.424	6.381	6.306	6.585	6.040	6.319	7.503
Lagged UNEMP	3.033	3.112							1.841	2.008
Lagged UEI			−1.131	−0.821					−1.157	−1.225
Lagged MP			−0.779	−0.674					0.307	0.272
Lagged RP			3.540	2.779					1.139	3.478
Lagged TS			0.675	0.812					0.328	0.155
Lagged EFC					0.396	0.488			0.639	1.048
EFC					−0.819	−1.234			−0.255	−0.250
Lagged LOTRET							1.774	2.196	0.789	0.920
LOTRET							3.825	3.912	3.766	4.043
Lagged MKTRET							2.469	1.968	1.061	0.913
MKTRET							0.047	0.042	−0.830	−0.823
Lagged EBSI									2.280	1.891
Number of Obs		71		71		71		71		70
Adjusted R^2		8.94%		18.15%		0.86%		16.23%		30.46%

Table VIII
Factor-Model Estimates for Lottery-Type Stock Portfolios

This table reports factor model estimates for the lottery-type stock portfolio. The lottery-type stock portfolio is formed at the end of each year and then held fixed throughout the following year. The following multi-factor time-series model is estimated:

$$\begin{aligned} LOTRET_t - R_{ft} &= \alpha + \beta_1 RMRF_t + \beta_2 SMB_t \\ &+ \beta_3 HML_t + \beta_4 UMD_t + \beta_5 LIQ_t + \beta_6 EBSI_t + \varepsilon_t \\ & \qquad t = 1, 2, \ldots, T. \end{aligned}$$

Here, $LOTRET_t$ is the rate of return on the lottery-type stock portfolio, R_{ft} is the riskfree rate of return, $RMRF_t$ is the market return in excess of the riskfree rate, SMB_t is the difference between the value-weighted return of a portfolio of small stocks and the value-weighted return of a portfolio of large stocks, HML_t is the difference between the value-weighted return of a portfolio of high B/M stocks and the value-weighted return of a portfolio of low B/M stocks, UMD_t is the difference between the value-weighted return of a portfolio of stocks with high returns during months $t-12$ to $t-2$ and the value-weighted return of a portfolio of stocks with low returns during months $t-12$ to $t-2$, LIQ_t is the innovation in aggregate liquidity in month t, $EBSI_t$ is the differential sentiment shift in month t, and ε_t is the residual return on the lottery-type stock portfolio. The retail investor data are from a large U.S. discount brokerage house for the 1991-96 time-period.

Intercept	RMRF	SMB	HML	UMD	LIQ	EBSI	Adj. R^2
0.395						0.300	
(0.516)						(3.000)	13.53%
0.607	1.096	2.376	1.176	−0.439	1.480		
(1.124)	(7.071)	(6.977)	(4.155)	(−2.697)	(0.093)		65.97%
−0.080	1.077	2.255	1.085	−0.333	1.298	0.104	
(−0.132)	(7.023)	(6.582)	(3.748)	(−2.056)	(0.084)	(2.557)	73.57%

Table IX

Differential Sentiment Shifts and Stock Returns: Vector Auto-Regression and Granger Causality Test Estimates

This table reports the vector auto-regression estimates and Granger causality test probabilities for the following vector auto-regressive model of order 1 (VAR(1)):

$$\begin{pmatrix} EBSI_t \\ LOTRET_t \end{pmatrix} = \begin{pmatrix} b_{10} \\ b_{20} \end{pmatrix} + \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \begin{pmatrix} EBSI_{t-1} \\ LOTRET_{t-1} \end{pmatrix} + \begin{pmatrix} \epsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

$EBSI_t$ is the *excess* change in the sentiment of investors in a given month and $LOTRET_t$ is the mean monthly return on lottery-type stocks. $EBSI$ is defined as, $EBSI_t = LBSI_t - OBSI_t$, where $LBSI_t$ is the buy-sell imbalance (BSI) of lottery stocks in month t and $OBSI_t$ is the buy-sell imbalance of other remaining stocks in month t. The BSI for portfolio p in month t is defined as, $BSI_{pt} = \frac{100}{N_{pt}} \sum_{i=1}^{N_{pt}} BSI_{it}$ where the BSI for stock i in month t is defined as $BSI_{it} = [\sum_{j=1}^{D_t}(VB_{ijt} - VS_{ijt}]/[(\sum_{j=1}^{D_t}(VB_{ijt} + VS_{ijt})]$. D_t is the number of days in month t, VB_{ijt} is the buy volume (measured in dollars) for stock i on day j in month t, VS_{ijt} is the sell volume (measured in dollars) for stock i on day j in month t, and N_{pt} is the number of stocks in portfolio p formed in month t. In Panel A, the auto-regression estimates for the 1991-96 period are reported and in Panel B, the probability matrix from Granger causality tests is shown where a matrix element represents the impact of column variable on the row variable. The retail investor data are from a large U.S. discount brokerage house for the 1991-96 time-period.

Panel A: Vector Auto-Regressive Model Estimates

Variable	Const	$EBSI_{t-1}$	$LOTRET_{t-1}$	Adj R^2
$EBSI_t$	−0.031	0.313	0.209	
	(−0.292)	(2.622)	(1.788)	16.85%
$LOTRET_t$	−0.015	0.235	−0.378	
	(−0.134)	(1.897)	(−3.099)	10.62%

Panel B: Granger Causality Probabilities

Variable	EBSI	LOTRET
$EBSI$	0.011	0.078
$LOTRET$	0.062	0.003

Table X
Gambling Intensity, Style Preferences, and Portfolio Performance

This table reports the raw and risk-adjusted performance measures of investor groups formed by sorting on gambling intensity. The mean factor exposures of their portfolios are also reported. Panel A compares mean performance levels of investors who invest in lottery-type stocks (i.e., "gamblers") with those who do not hold lottery-type stocks even once during the sample-period (i.e., "non-gamblers"). The four-factor alpha and the factor exposures are obtained by fitting a four-factor time-series model to the monthly portfolio returns series of each investor over the period the investor is active. Panel B reports the mean performance measures and the mean factor exposures for investor groups formed by sorting on the mean weight in lottery-type stocks. The retail investor data are from a large U.S. discount brokerage house for the 1991-96 time-period. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Performance of Gamblers versus Non-Gamblers

Lottery Stocks	Performance Measures				Factor Exposures			
Weight Decile	4F Alpha	Mon Ret	Std Dev	Sharpe	RMRF	SMB	HML	UMD
Non-Gambler	−0.148	1.227%	7.386%	0.117	1.143	0.442	0.043	−0.237
Gambler	−0.637	1.189%	9.762%	0.087	1.236	1.270	0.370	−0.407
G−NG	−0.489***	−0.039**	2.376***	−0.031***	0.093***	0.828***	0.327***	−0.170***

Panel B: Performance of Heavy versus Mild Gamblers

Lottery Stocks	Performance Measures				Factor Exposures			
Weight Decile	4F Alpha	Mon Ret	Std Dev	Sharpe	RMRF	SMB	HML	UMD
Mild Gambler	−0.176	1.432%	7.352%	0.144	1.233	0.650	0.103	−0.232
D2	−0.287	1.376%	8.259%	0.124	1.241	0.896	0.161	−0.313
D3	−0.400	1.322%	8.796%	0.107	1.252	1.023	0.214	−0.349
D4	−0.586	1.300%	9.477%	0.096	1.271	1.225	0.359	−0.379
D5	−0.560	1.285%	9.762%	0.092	1.262	1.298	0.360	−0.408
D6	−0.714	1.150%	10.072%	0.076	1.233	1.327	0.396	−0.404
D7	−0.714	1.199%	10.460%	0.078	1.257	1.476	0.461	−0.480
D8	−0.966	1.004%	11.027%	0.054	1.239	1.561	0.509	−0.475
D9	−0.968	0.931%	11.506%	0.045	1.210	1.695	0.582	−0.558
Heavy Gambler	−1.273	0.684%	11.962%	0.023	1.127	1.808	0.696	−0.548
Heavy−Mild	−1.097***	−0.748***	4.610***	−0.121***	−0.106***	1.159***	0.593***	−0.316***

Table XI

Portfolio Under-performance Estimates Across Income Categories

This table reports the raw and risk-adjusted performance measures of investor groups formed by sorting on income and gambling behavior. Panel A reports the mean performance levels of gamblers (i.e., investors who invest in lottery-type stocks) within different income groups. Panel B reports the mean performance levels of non-gamblers (i.e., investors who do not hold lottery-type stocks even once during the sample-period) within different income groups. The four-factor alpha is obtained by fitting a four-factor time-series model to the monthly portfolio returns series of each investor over the period the investor is active. Portfolio size is the mean of the mean portfolio sizes of investors within an income group. The annual portfolio under-performance is obtained by multiplying the four-factor alpha with the portfolio size. The retail investor data are from a large U.S. discount brokerage house for the 1991-96 time-period.

Panel A: Performance Measures for Investors who Invest in Lottery-Type Stocks

	Annual Income								
	<15K	15-20K	20-30K	30-40K	40-50K	50-75K	75-100K	100-125K	>125K
Four-Factor Alpha	−1.104	−0.908	−0.670	−0.646	−0.788	−0.846	−0.866	−0.747	−0.779
Mean Mon Return	0.85%	0.90%	1.10%	1.15%	1.06%	1.00%	1.02%	1.06%	1.06%
Standard Deviation	10.25%	9.87%	9.72%	10.20%	9.72%	9.98%	10.13%	9.99%	9.79%
Sharpe Ratio	0.053	0.057	0.079	0.080	0.077	0.066	0.069	0.075	0.077
Portfolio Size	$35,676	$23,910	$27,312	$30,532	$38,113	$39,052	$34,376	$41,598	$45,463
Annual Under-Perf	$4,725	$2,604	$2,194	$2,365	$3,606	$3,963	$3,572	$3,729	$4,250
UPerf (% of Income)	31.50%	13.02%	7.31%	5.91%	7.21%	5.28%	3.57%	2.98%	1.70%
Num of Investors	198	129	325	517	543	1,320	1,274	809	607
% of Inc Group	23.62%	22.18%	22.59%	21.22%	20.71%	20.25%	19.42%	17.78%	18.38%

Panel B: Performance Measures for Investors who do not Invest in Lottery-Type Stocks

	Annual Income								
	<15K	15-20K	20-30K	30-40K	40-50K	50-75K	75-100K	100-125K	>125K
Four-Factor Alpha	−0.337	−0.346	−0.352	−0.312	−0.210	−0.263	−0.239	−0.250	−0.190
Mean Mon Return	1.17%	1.27%	1.19%	1.21%	1.22%	1.22%	1.31%	1.23%	1.27%
Standard Deviation	7.94%	8.05%	7.75%	8.03%	7.81%	8.07%	8.30%	8.16%	8.17%
Sharpe Ratio	0.100	0.115	0.110	0.105	0.112	0.108	0.114	0.109	0.112
Portfolio Size	$33,752	$28,952	$33,297	$30,765	$28,647	$26,264	$30,861	$32,257	$34,646
Annual Under-Perf	$1,364	$1,201	$1,407	$1,153	$721	$827	$886	$969	$788
UPerf (% of Income)	9.09%	6.00%	4.69%	2.88%	1.44%	1.10%	0.89%	0.77%	0.31%

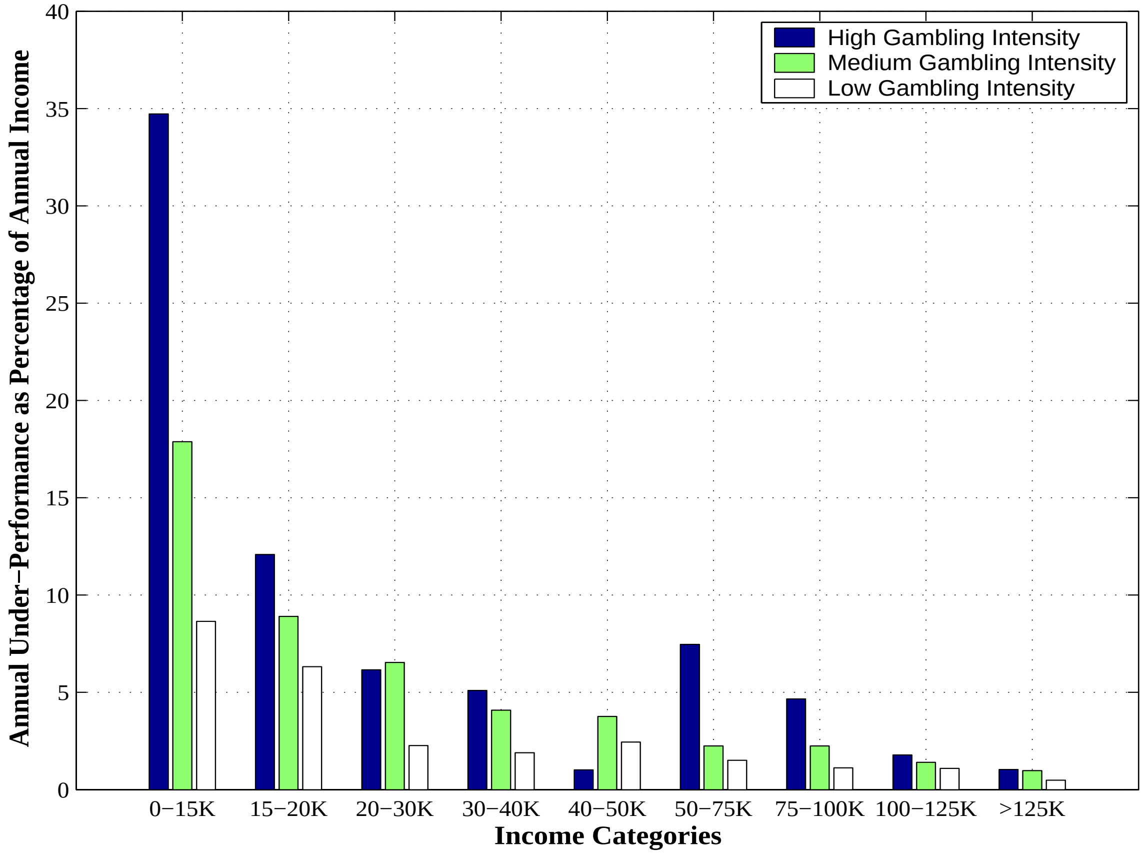

Figure 1. Gambling intensity and annual risk-adjusted under-performance across income categories. This figure shows the annual risk-adjusted under-performance as a percentage of income for low, medium, and high intensity gamblers within each income category. Gamblers (i.e., investors who invest in lottery-type stocks) are divided into three categories based on their portfolio weight in lottery type stocks. Investors whose portfolio weights are in deciles 1-3, 4-7, and 8-10 are identified as low, medium, and high intensity gamblers, respectively. The individual investor data are from a large U.S. discount brokerage house for the 1991-96 time-period.