Priming and Stock Preferences: Evidence from IPO Lotteries*

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Abstract

Existing studies in social psychology have found that priming has pervasive effects, mostly in laboratory settings and over short periods of time. This study investigates the priming effect in the real financial world and over longer periods of time. We hypothesize that successful lottery-like experiences raise investors' subsequent demand for other lottery-like stocks by increasing the accessibility of tail events. By exploiting the randomized distribution of IPO shares in China as a natural experiment, we find that, compared with matched control investors, the investors who were allocated IPO shares (lottery winners) substantially shift their non-IPO portfolios toward lottery-like stocks over the three months subsequent to the distribution. This effect is more pronounced for investors winning IPO lotteries with lower winning rates or larger issue-price discounts. Moreover, lottery winners experience a decrease in their overall portfolio return by more than 1% within the three months subsequent to the distribution relative to matched control investors, which is largely in proportion to the increases in their subsequent demand for lottery-like stocks. Our findings are not explained by the house money effect or the wealth effect. Overall, our study suggests that lottery-like cues play a critical role in shaping investors' gambling preferences in stock markets, providing field-based evidence for the long-term priming effect.

JEL Classification: G41, G11, G14
Key Words: priming; preferences; lottery; IPO

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Abstract

Existing studies in social psychology have found that priming has pervasive effects, mostly in laboratory settings and over short periods of time. This study investigates the priming effect in the real financial world and over longer periods of time. We hypothesize that successful lottery-like experiences raise investors' subsequent demand for other lottery-like stocks by increasing the accessibility of tail events. By exploiting the randomized distribution of IPO shares in China as a natural experiment, we find that, compared with matched control investors, the investors who were allocated IPO shares (lottery winners) substantially shift their non-IPO portfolios toward lottery-like stocks over the three months subsequent to the distribution. This effect is more pronounced for investors winning IPO lotteries with lower winning rates or larger issue-price discounts. Moreover, lottery winners experience a decrease in their overall portfolio return by more than 1% within the three months subsequent to the distribution relative to matched control investors, which is largely in proportion to the increases in their subsequent demand for lottery-like stocks. Our findings are not explained by the house money effect or the wealth effect. Overall, our study suggests that lottery-like cues play a critical role in shaping investors' gambling preferences in stock markets, providing field-based evidence for the long-term priming effect.

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I. Introduction

Traditional portfolio theory suggests that investors' demand for stocks is determined by stock return dynamics and investors' utility function. Investors' prior experiences should not affect their demand beyond their effect on current state variables such as the wealth level. Studies in social psychology, however, find that priming effects and prior experiences have a very broad influence over human behavior. External cues can unconsciously activate associated mental concepts in memory and increase the accessibility of perceptually or conceptually related concepts in subsequent decisions. For example, North, Hargreaves, and McKendrick (1997) show that in-store music affects consumers' wine choices. The demand for French (German) wine is higher than usual when French (German) music is played. Priming effects have been demonstrated in a wide range of behaviors.[1] In this paper, we examine the priming effect in the stock market by investigating whether prior (successful)lottery-like experiences can influence investors' stock preference for lottery-like stocks (hereinafter "gambling preference"), beyond their influence on the wealth level and on the underlying dynamics of asset returns under rational expectations.

In particular, we argue that winning a lottery, like other cues, is an opener concept, which tends to increase the accessibility of related concepts such as the tail events of *other* lottery-like stocks. In addition, an increased accessibility of tail returns is also likely to cause investors to weight tail returns more heavily when making investment decisions, probably because of availability bias or the psychological principle that what is focal is important.[2] Thus, investors may think of lottery-like assets as being more appealing than before, and this raises their demand for these lottery-like assets. As a result, a lottery-winning experience tends to increase investors' demand for *other* lottery-like assets.

To investigate the priming effect in the stock market, we exploit both investors' experiences of winning randomized IPO lotteries in the Chinese stock market and detailed account-level trading records. In China, owing to excess demand, IPO shares are distributed to retail investors who applied for them using randomized lotteries. Moreover, for institutional reasons, prices of IPO shares are largely discounted and are expected to rise spectacularly in the aftermarket. In the natural experiment, retail investors are randomly assigned to be exposed to IPO lottery success (an external cue). This approach allows us to obtain a difference-in-difference estimate on the effect of a randomized exposure to lottery-like cues on subsequent gambling propensity by comparing allocated versus non-allocated investors' subsequent trading behaviors in the stock market. In addition, our sample covers 685 IPO firms, in which variations in lottery rates and the price discount of IPO shares warrant the exploration

[1] Bargh (2006 and 2014) and Wheeler and DeMarree (2009) provide excellent reviews on priming effects. Recent studies, however, find that some of the previous studies on priming cannot be replicated (see, e.g., Yong (2012)), especially the longer-term effect. In response, Meyer (2014) confirms that the short-term priming effect is still well established. In addition, Bargh (2014) responds to the replication crisis by reviewing recent examples in natural settings. We provide more detailed discussions in the section on literature and hypothesis development.

[2] See Morewedge and Kahneman (2010) for excellent reviews.

of cross-sectional patterns of the effect induced by lottery-like stimuli. Moreover, the randomness in IPO lotteries facilitates casual inferences.

To examine changes in investors' gambling propensity in stock markets, we first follow the literature to calculate a lottery index (Kumar, 2009; Han and Kumar, 2013) and maximum daily return (hereafter MAX; Bali, Cakici, and Whitelaw (2011)) to proxy for stock-level lottery attributes, respectively, and then aggregate the average lottery attributes of all non-IPO stocks that an investor purchases in a given month to approximate account-level gambling propensity.

Our main findings are summarized as follows. First, we find that exogenous exposure to IPO lottery success strongly increases treated investors' propensity to gamble in stock markets, causing lottery winners to substantially tilt their portfolios toward lottery-like stocks relative to IPO lottery losers. Specifically, compared with IPO lottery losers, the gambling propensity of IPO lottery winners increases by 18% of its mean value prior to the event. These results are robust when controlling for investor characteristics, account and time fixed effects, and double clustering standard errors by account and time. Our findings confirm that randomized exposure to lottery-like cues can substantially increase investors' gambling propensity in that they shift their non-IPO portfolios toward lottery-like stocks.

Second, we examine whether the effect induced by exposure to lottery-like cues on gambling behaviors varies with the salience of the cue. Because the activation of memory may be affected by the salience of the cue, we expect that increases in gambling propensity will be more pronounced when the salience of the lottery-like cue increases. In the context of an IPO lottery, winning an IPO security that has a lower success rate or a larger price rise in the aftermarket (i.e., a higher price discount) makes treated investors more likely to be influenced by lottery-like stimuli. Indeed, we find that increases in treated investors' gambling behaviors are negatively related to their success rates in IPO lotteries but positively related to price run-ups in the aftermarket, suggesting that lottery-like cue salience accounts for changes in trading behaviors around IPO lottery success.

Furthermore, we exploit the difference-in-difference approach to evaluate changes on investors' portfolio performance before and after IPO shares are randomly allocated, which sheds light on the economic consequences of changes in trading behaviors induced by external lottery-like cues. On average, IPO lottery winners' overall portfolio returns decrease by more than 1% in the three-month period following the IPO allocation, relative to IPO lottery losers. More importantly, the decreases in investors' portfolio performance are significantly associated with increases in gambling propensity but not significantly associated with increases in turnover, indicating that it is the increased gambling behaviors rather than other factors that lead to wealth losses. Overall, our findings suggest that gambling behaviors induced by external lottery-like cues are costly for retail investors and exacerbate their underperformance.

One alternative explanation is that increased gambling behaviors just result from increases in risk preferences after experiencing IPO lottery gains. Two possible reasons may account for the associated changes in investors' risk attitudes around IPO lottery success. One is the wealth effect, which implies that winning IPO shares increases one's wealth and thus one's risk-bearing capacity. The other is the house money effect (e.g., Thaler and Johnson, 1990), which argues that investors create a separate "mental account" for their winnings in stock markets, and they are willing to increase their level of risk taking with these winnings.

While completely differentiating between these alternative channels is difficult for us, we obtain several pieces of evidence that are difficult to reconcile with the possibility that changes in investors' risk preferences completely drive our results. First, we directly compare the effect of gains from IPO lotteries on investors' subsequent gambling propensity with that of the prior performance of non-IPO stocks. While—consistent with the house money effect—investors have an increasing gambling propensity after they make money in stock markets, its magnitude is much smaller than that of profits from IPO lotteries, suggesting that the house money effect cannot fully explain the effect of winning an IPO lottery on subsequent gambling propensity. In addition, we find that subsequent increases in gambling behaviors are more pronounced when investors win IPO lotteries with lower success rates or larger underpricing. These cross-sectional variations still hold when controlling for proxies for the house money effect, further mitigating the concern that the house money effect drives our results.

In addition, the average gain from an IPO lottery is 5,100 yuan, which is quite small relative to the average account asset of 118,700 yuan. This fact makes it unlikely that winning an IPO lottery is somehow relieving a wealth constraint that causes a different change in behavior across IPO lottery winners and losers. Moreover, we find that even for investors with an average portfolio size in excess of 1 million yuan, IPO lottery success continues to produce economically and statistically significant effects on the subsequent demand for lottery-like stocks. Interestingly, the effect of a successful IPO lottery experience appears to be stronger for larger accounts in some cases, contrary to the prediction of the wealth effect. Lastly, the subsequent underperformance of IPO winners is also inconsistent with the increased risk tolerance due to the wealth effect under a purely rational framework since there is a positive risk-return trade-off under such a framework.

Our study is clearly related to the large literature on priming in social psychology. Although short-term (e.g., a few seconds to a few minutes) associative priming is well established (see, e.g., Meyer (2014)), some longer-term priming effects cannot be replicated in subsequent studies, casting doubts on the integrity of psychological research (see, e.g., Yong (2012) and Molden (2014)). In particular, Nobel laureate Daniel Kahneman has written an open letter to the community to call on priming researchers to check the robustness of their findings. Other critics have claimed that priming studies suffer from major publication bias (see, e.g., Bower (2012) and Doyen, Klein, Pichon, and Cleeremans (2012)). Thus, our study provides field-based evidence supporting the long-term effect of priming.

Our study also contributes to the literature that explores how personal experiences influence decision making in financial markets. For example, some empirical studies examine how disaster experiences (catastrophic fatal events) affect people's risk preferences and corporate managers' risk-taking behavior (see, e.g., Gallagher, 2014; Koudijs and Voth, 2016; Bernile, Bhagwat, and Rau, 2017; Dessaint and Matray, 2017, Gao, Liu, and Shi, 2019). Malmendier and Nagel (2011) and Knüpfer, Rantapuska, and Sarvimäki (2017) also document that people who experienced macroeconomic shocks were less likely to participate in a risky financial market. In addition, Huang (2019) documents that prior success in a given industry increases the likelihood of subsequent purchases in the same industry. In this paper, we find that experiences with IPO lottery success significantly increase investors' preference for other lottery-like stocks, which also highlights the role of personal experiences in shaping one's investment decisions. However, most prior studies measure experiences in a very indirect way that relies heavily on variations in age cohorts, locations, or occupations, which are unavoidably contaminated by unobserved demographic or geographic factors. In this paper, we exploit randomized exposure to IPO lottery success to explore the effect of experiences, an approach that not only precisely defines the treated group but also facilitates causal inferences. In addition, our study highlights the role of priming in stock investment, which makes related concepts more accessible.

Several papers in the literature also explore the effect of experience with IPO lottery success. Kaustia and Knüpfer (2008) find a strong, positive link between personally experienced IPO returns and future subscriptions at the investor level in Finland. Chiang, Hirshleifer, Qian, and Sherman (2011) exploit 84 IPO auctions in Taiwan and document that while higher returns in previous IPO auctions increase the likelihood of bidders participating in future auctions, bidders' returns decrease with experiences because of deteriorating selection ability and more aggressive bidding strategies. Both studies look at the relationship between prior IPO experiences and subsequent participation in IPO activities. In contrast, we explore how IPO lottery success experiences influence other conceptually related investment decisions (i.e., preferences for lottery-like stocks).

More recently, Anagol, Balasubramaniam, and Ramadorai (2019) and Gao, Shi, and Zhao (2018) demonstrate that randomized IPO gains cause winning investors to substantially increase portfolio trading in non-IPO stocks relative to lottery losers in India and China, respectively, probably because of increased overconfidence. In exploring the underlying mechanism, these studies highlight the role of psychological biases (e.g., reinforcement learning, undue optimism after receiving good returns) in learning from personal experiences. On the other hand, our study highlights that successful IPO lottery experiences directly increase the accessibility of tail returns and cause investors to overweight tail returns in subsequent conceptually related investment decisions. Moreover, we show that the subsequent underperformance of IPO lottery winners is positively related to the increased preferences for lottery-like stocks and negatively related to the increased turnover, once we control for the changes in preferences for lottery-like stocks.

In addition, for a typical randomized distribution of IPO shares in China, the probability of winning IPO shares is very low (0.73%), but the cumulative return of IPO shares up until the first day of not hitting their price limits is as high as 58% (around 750 US dollars), suggesting that the return profile of applying for IPO shares is indeed similar to lottery characteristics. However, for a typical randomized distribution of IPO shares in India, the probability of winning IPO shares is relatively high (37%), and the return from the IPO discount is 17.13% (amounting to only 24.78 US dollars).[3] Therefore, compared with India, the setting in China is more appropriate for being exploited to explore the impact of lottery-like cues on investors' trading behaviors.

Lastly, our study is also related to the large finance literature on preference for lotteries and its asset pricing implications. Experimental and theoretical studies suggest that individuals tend to overweight low-probability events, particularly those with extreme payoffs, since they are more salient (e.g., Kahneman and Tversky, 1979; Tversky and Kahneman, 1992; and Bordalo, Gennaioli, and Shleifer, 2012). A large strand of empirical literature demonstrates that retail investors indeed exhibit a preference for lottery-like stocks (Kumar, 2009; Han and Kumar, 2013). In addition, Barberis and Huang (2008) propose a model in which investors who overweight tail returns in decision making would be willing to pay higher prices for lottery assets and require lower returns for such assets. Indeed, gambling preferences can not only influence asset prices (e.g., Boyer, Mitton, and Vorkink, 2009; Bali, Cakici, and Whitelaw, 2011; Amaya, Christoffersen, Jacobs, and Vasquez, 2015), but also account for a range of asset pricing puzzles.[4] However, most existing studies tend to focus on the unconditional preferences for lottery-like stocks, leading to overpricing of these stocks.[5] In this paper, we ask whether prior IPO lottery experiences increase the accessibility of the lottery-like concept and thus induce time variation in demand for lottery-like assets. That is, while most studies focus on the unconditional overweighting of tail events, we examine whether the tendency of overweighting changes with environmental exposure.

II. Institutional Backgrounds

In China, retail investors are allowed to bid IPO shares at a fixed price that is determined by underwriters after taking into account the result of book building among qualified investors. Given that retail investors almost always oversubscribe IPO shares, a lottery procedure is run to determine the allocation among retail applicants.

Specifically, for each IPO in the Shanghai (Shenzhen) Stock Exchange, retail investors with an average stock portfolio worth at least 10,000 (5,000) RMB on day t-20 to day t-2 relative to the IPO offer day can apply for an IPO allotment in Shanghai (Shenzhen). Each 10,000 (5,000) RMB qualifies for one allotment ticket that corresponds to 1,000 (500) IPO shares in Shanghai (Shenzhen). Retail investors who applied for an IPO allotment will be assigned an IPO application number for each

[3] All these numbers are from Panel B of Table 1 in Anagol, Balasubramaniam, and Ramadorai (2019).
[4] Gambling preference exists in IPO performance (Green and Hwang, 2012), over-the-counter stocks (Eraker and Ready, 2015), distressed stocks (Conrad, Kapadia, and Xing, 2014; An, Wang, Wang, and Yu, 2019), out-of-the-money options (Byun and Kim, 2016), and beta anomaly (Bali, Brown, Murray, and Tang, 2017).
[5] There are a few exceptions. For example, Liu, Wang, Yu, and Zhao (2019) and An, Wang, Wang, and Yu (2019) investigate the time variation in preferences for lottery and the cross-sectional heterogeneity in the preferences for lottery, respectively.

allotment ticket (with each application number corresponding to 1,000 (500) shares in Shanghai (Shenzhen)). Investors with more capital can apply for more than one allotment ticket as long as the total allotment application is less than 0.1% of the total IPO shares. In this sense, the likelihood of winning the IPO allotment may be positively associated with investors' wealth. Investors will learn their application results on day t+2. The IPO application number is randomly assigned by the China Securities Depository and Clearing Corporation (CSDC) and cannot be changed. The winning allotment numbers are drawn randomly from the pool while the entire process is digitally recorded and audited.

In our sample period, Firms' IPO in China adopted two different pricing models for the issue price. Prior to 2014, the issue price was determined by the underwriter by combining IPO firms' financing needs and institutional bids during the book-building process. The underpricing of IPO shares is moderate, about 28%, which is generally comparable to the case in the United States. Since 2014, the China Securities Regulatory Commission (CSRC) has never approved IPOs with a valuation of more than 23x the price-to-earnings (PE) ratio, and most IPO firms issue shares at a price that just makes the ratio of the issue price over current earnings per share below the 23x cap. Moreover, after 2014, the CSRC not only has limited the issue price of IPO shares but also started introducing first-day price movement limits of IPO shares in the secondary market. Given these changes, IPO underpricing after 2014 will be underestimated if measured using the close price of the first trading day of IPO shares. A more reasonable measure is to calculate the issue-price discount using the close price of the first day when stock prices are not subject to price movement limits after listing. Under these new rules, the underpricing of China's IPO shares rose to over 100%, and applicants could make a very considerable amount of money if they won the allotment. Therefore, it is not surprising that the greater underpricing has attracted more retail investors to apply for IPO shares, which has lowered the average success rate of IPO lotteries from 2.25% prior to 2014 to 0.7% after 2014.

Overall, for retail investors, applying for IPO shares in China is a kind of lottery-like investment in the sense that it offers an opportunity to obtain a low probable but huge return. Therefore, the allotment of IPO shares is akin to an exogenous experiment in which lottery winners experience huge returns and lottery losers get nothing. Moreover, the average winning rates and investment returns (i.e., the price run-up after listing) vary across IPO events, which warrants the explorations of cross-sectional patterns of the effect induced by the experience of winning an IPO lottery.

III. Literature and Hypothesis Development

Does the weight investors allocate to tail events change with external cues? Or more generally, does investors' value function in decision making under uncertainty vary with environmental cues? The research in social psychology has a long history of exploring related issues. First, we will briefly review related research in social psychology, and then, we build our own hypotheses.

1. Related literature in psychology

External cues can activate certain information and increase a person's ability to recall the information in subsequent conceptually related judgments. Psychological research has demonstrated that external cues, also called "primes," can automatically activate associated representations in memory, leading the memories to become more accessible. Moreover, this activation can also automatically spread to related concepts through an associative network (Morewedge and Kahneman, 2010). A well-established concept in the consumer psychology literature is that cue exposure can affect consumers' choices not only toward directly exposed goods but also toward products that are conceptually related to primes (Berger and Fitzsimons, 2008).

Accessibility plays a crucial role in the well-documented priming effect. The psychology literature has used the term "priming" to refer to several distinct phenomena that share similar underlying mechanisms. Exposure to some prior event—the cue—increases the accessibility of the same stimulus and related concepts in memory, resulting in a greater likelihood of retrieval. Priming effects have been demonstrated in a wide range of behaviors, such as product choices (North, Hargreaves, and McKendrick, 1997; Mandel and Johnson, 2002), voting (Berger, Meredith, and Wheeler, 2008), helping behavior (Over and Carpenter, 2009), lifestyles (Papies, 2016), and saving behaviors (DeVoe, House, and Zhong, 2013 Choi et al., 2017). In all of these effects, primes make mental concepts accessible, and these mental concepts then direct behavior (Wheeler and DeMarree, 2009; Bargh, 2014).

More interestingly, primes not only generate short-term changes in the accessibility of related information but also have the potential to change memory representation in a more permanent fashion. For example, using picture naming tests, Cave (1997) demonstrates that the priming effect could be detected several months (between 6 and 48 weeks) after the initial exposure, suggesting that a single stimulus has a very long-lasting effect. Mitchell (2006) demonstrates that treated agents with a brief exposure to target pictures 17 years ago exhibit significantly higher identification rates than control agents in picture fragments identification tests. Since temporary activation is inadequate to account for these phenomenal long-term priming effects, psychologists prefer to interpret the priming effect as a form of implicit memory that has been differentiated from the faster decay of explicit memory.

On the other hand, subsequent studies cannot replicate some earlier findings on priming effects, especially those related to longer-term priming effects (see, e.g., Yong (2012) and Doyen, Klein, Pichon, and Cleeremans (2012)). These skepticisms have questioned not only the existing evidence of the priming effect but even whether the mechanisms through which priming occurs are psychologically plausible (Molden, 2014). This replication crisis has prompted Nobel laureate Daniel Kahneman to write an open letter to the community to call on priming researchers to check the robustness of their findings.[6] Our study joins this debate by investigating the long-term effect of priming in the field.

Based on earlier research in social psychology, we propose a hypothesis that investors would have

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[6] Ed Yong, "Nobel laureate challenges psychologists to clean up their act," *Nature*, October 3, 2012, doi:10.1038/nature.2012.11535.

increased preferences for attributes that have been activated by external stimulus directly or indirectly. In terms of decision-making language, Morewedge and Kahneman (2010) state, "Strongly activated information is likely to be given more weight than it deserves and relevant knowledge that is not activated by the associative contexts will be underweighted or neglected." These principles reflected in priming and associative activation shed light on our analyses concerning whether and how investors' gambling propensity varies with environmental cues. In fact, anything that draws focused attention can lead its observers to overestimate its importance. Daniel Kahneman coined this effect as the "focusing illusion."[7]

2. Hypothesis development

IPO lotteries and lottery-like stocks are conceptually related, though not identical. In China, retail investors are allowed to bid on IPO shares at a fixed price that is determined by underwriters after taking into account the result of book building among qualified investors. Given that retail investors almost always oversubscribe IPO shares, a lottery procedure is run to determine the allocation among retail applicants. For retail investors, bidding on IPO shares and investing in lottery-like stocks are similar in the sense that in both cases, investors have a low probability of gaining an extremely positive return. The success rate in IPO lotteries is very low (1.47%), but the average return of IPO shares is extremely large (86%) in our sample, suggesting that the return profile of participating in IPO lotteries is indeed similar to the characteristics of lottery-like stocks.

We hypothesize that IPO lottery success generates positive influences on retail investors' preference for other lottery-like stocks. First, IPO lottery success makes investors more likely to pay attention to lottery-like stocks because of their conceptual relation to the IPO lottery. Suppose that investors are considering which kind of stocks to invest in. We argue that IPO lottery winners are more likely to note lottery-like features (e.g., positive skewness, maximum daily return) among various attributes of a stock (such as value, growth potential, profitability, prior price run-up, and so on) than IPO lottery losers, possibly because the success in IPO lotteries is more likely to remind investors of the attractiveness of lottery-like stocks. When investors pay more attention to lottery-like stocks, they are more likely to buy these stocks (Barber and Odean, 2008). However, attention is a necessary, but not sufficient, condition that breeds investments in lottery-like stocks.

More important, exposure to IPO lottery success increases investors' ability to recall tail returns, thereby inducing investors to give more weight to conceptually related attributes. The success in lPO lotteries enables investors to realize extremely large profits from lottery-like investments, which helps them to construct vivid memories of the potential upside of lotteries. Building on social psychology research, we argue that the experience of winning IPO shares serves as a cue or stimulus, which increases investors' ability to recall positive tail returns (i.e., a lottery-like feature). As mentioned by

[7] In his book *Thinking, Fast and Slow*, Daniel Kahneman writes that "nothing in life is as important as you think it is while you are thinking about it." He thinks that the concept, appreciated properly, can improve everyone's understanding of the world.

Kahneman and Tversky (1979), people have limited ability to comprehend and evaluate extreme probabilities, so highly unlikely events are either ignored or overweighted. People who have no experience with tail returns are likely to ignore tail returns and are thus reluctant to invest in lottery-like stocks because they do not have any relevant memory. On the contrary, exposure to IPO lottery success activates investors' memories of tail returns and facilitates the processing of related information. Consequently, the resultant ease of processing conceptually related information can cause investors to give more weight to lottery-like features (attributes contained in the cue) when making investment decisions. Therefore, we predict that compared with lottery losers, lottery winners will put more weight on tail returns and thus exhibit a greater preference for lottery-like stocks.

In addition, according to the focusing illusion, when investors pay more attention to lottery-like stocks, these stocks are more appealing and more important to them. Consequently, these investors may overestimate the probability of tail events and thus drive up the demand for these stocks. As a result, the focusing illusion provides another corroborating force for increasing the demand for lottery-like stocks after winning an IPO lottery.

IV. Empirical Design

1. Baseline regressions

We can view the randomized allocation in each IPO lottery as a separate experiment with different average success rates. The idea of our empirical specification is to pool all of these experiments to maximize statistical power while ensuring that we exploit only the randomized variation of treatment status within each IPO lottery. Basically, we run OLS regressions by pooling treated and control investors in different experiments into a single dataset with a fixed effect for each IPO lottery. These IPO lottery event fixed effects ensure that our identification of the treatment effect stems only from the random variation in allocation within each IPO lottery.

Specifically, we estimate the causal effect of the experience of winning an IPO lottery on investors' gambling propensity by running the following baseline regressions:

$$Gambling_{ijt} = \beta_0 + \beta_1 Treat_{ijt} + \beta_2 Post_{jt} + \beta_3 Treat_{ijt} * Post_{jt} + \gamma_j + Controls + \varepsilon_{ijt} \quad (1)$$

Here, $Gambling_{ijt}$ is a measure of gambling propensity for investor i in IPO event j at calendar month t. The variable $Treat_{ijt}$ is an indicator variable that takes the value of one if investor i was allocated shares in the lottery for IPO event j (treated sample) and zero otherwise (control sample). The variable $Post_{jt}$ is an indicator variable that takes the value of one if calendar month t is within three months after winning the IPO j' allotment and zero if calendar month t is within three months prior to winning the IPO j' allotment. The coefficient of the interaction item ($Treat_{ijt} * Post_{jt}$), β_3, is of great interest, since it captures the differences in treated investors' gambling behaviors before and after the IPO lottery event relative to similar differences among control investors. It captures the net treatment effect after controlling for common time-series variations of gambling behaviors in control groups.

The variable γ_j is the fixed effect associated with each IPO lottery event. Conditional on the inclusion of these fixed effects, the estimation of β_3 only exploits the variation within each randomized experiment, which identifies β_3 as the casual impact of the experience of winning the IPO lottery on investors' gambling behaviors. Our estimated effect is essentially a weighted average of the treatment effects from each separate experiment. Intuitively, the regression weights give more importance to IPO lotteries with a larger sample size (i.e., those involving more retail investors).

To increase the statistical precision of our estimates, we further include account-level time-varying control variables and additional fixed effects. We control for investors' portfolio value (measured at the beginning of each month) and monthly portfolio turnover. While the difference-in-difference setting examines changes in investors' gambling behaviors that should not be affected by time-invariant factors, we still include the account fixed effect (γ_i) to soak up the influence of time-invariant factors (e.g., investors' demographic information). We also include IPO event month (γ_{jt}) or calendar month (γ_t) fixed effects to control for variations induced by particular periods (i.e., stock market boom and bust). Note that after controlling for account and IPO event month fixed effects, the variables $Treat_{ijt}$ and $Post_{jt}$ will be omitted because they are absorbed by the fixed effects.

All standard errors are clustered by account. To handle correlations of different investors in the same calendar month, in robustness checks we further cluster standard errors by account and by calendar month.

2. Gambling propensity

This paper measures investors' gambling propensity by looking at the lottery characteristics of stocks in their portfolio. The general idea is to first compute lottery characteristics for each stock and obtain an investor's gambling propensity by aggregating the weighted average lottery feature of all stocks that the investor purchases in a given month with dollar purchases on each stock as the weight. Following the literature (e.g., Han and Kumar, 2013), we exploit the composite lottery index (Lottery) to measure the lottery characteristics for each stock.[8] In particular, investors' gambling propensity in a given month is constructed through the following steps:

First, we calculate the lottery characteristics for each stock in each month. Following Han and Kumar (2013), the lottery index of a stock in a given month ($Lottery_{st}$) is defined as the sum of the

[8] Kumar (2009) argues that investors with gambling desires prefer stocks with lower nominal prices, higher idiosyncratic skewness, and higher idiosyncratic volatility. Han and Kumar (2013) exploit the three characteristics to construct a composite lottery index to measure lottery-like features of stocks. In addition, Bali, Cakici, and Whitelaw (2011) posit that maximum daily return (MAX) captures the key feature of lottery-like stocks (extreme positive return) and argue that investors tend to perceive stocks with a larger MAX in history as having a higher likelihood of experiencing extremely positive returns owing to extrapolation biases. We also measure investors' gambling propensity using MAX and replicate our main analyses. The results (See Table A1) are quite similar, indicating that our findings are not sensitive to measures for investors' gambling propensity.

vigintile assignments to its idiosyncratic volatility, idiosyncratic skewness, and nominal stock price. Nominal stock price is the average daily closing stock price in that month. Idiosyncratic volatility is the volatility of the residual obtained from regressing the firm's daily returns on corresponding Fama and French three factors and the momentum factor. Idiosyncratic skewness is the third moment of the residual obtained by fitting a two-factor model (market returns and the square of market returns). Idiosyncratic volatility and idiosyncratic skewness are both estimated using daily returns over the past six months.

Second, for each investor, we calculate the dollar volume weighted average lottery characteristics of all stocks that the person has purchased in each month as the account-level gambling propensity in that month ($Lottery_{it}$). Particularly, we only include non-IPO stocks in gauging investors' gambling propensity:

$$Lottery_{it} = \sum_{s=1}^{N_{i,t}} w_{ist} * Lottery_{st} \tag{2}$$

Here, w_{ist} is the weight of stock *s* for investor *i* at month *t* and $N_{i,t}$ is the number of stocks that investor *i* purchased at month *t*.

Third, given that the Chinese stock market undergoes huge boom and bust periods during our sample period, to make investors' gambling propensity comparable across different periods, we standardize an investor's gambling propensity obtained in the second step (subtracting the average gambling propensity of all investors and then dividing by their standard deviation within each month). Finally, we examine the changes in standardized gambling propensity before and after the IPO lottery for both treated and control investors.

3. Moderating effect

We further examine whether the impact of the experience of winning the IPO lottery on investors' gambling propensity varies with the characteristics of randomized cue exposure. We explore cross-sectional patterns of the main effects by running the following regressions among treated investors:

$$Gambling_{ijt} = \alpha_0 + \alpha_1 Post_{jt} + \alpha_2 Salience_j + \alpha_3 Salience_j * Post_{jt} + Controls + \varepsilon_{ijt} \tag{3}$$

Here, $Salience_j$ is measured by either the average success rate or the IPO price discount. We will elaborate on definitions of these variables in Section VI.3. We expect that investors who are exposed to more salient IPO lotteries are more likely to be affected.

4. Portfolio performance

We follow Barber and Odean (2000) to calculate changes in portfolio performance before and after the IPO lottery for treated and matched control investors. Unlike Barber and Odean (2000), however, we calculate portfolio returns on a daily basis instead of a monthly frequency. Similarly, the method also bears the following two assumptions. First, all stocks are purchased at the close price on day t and sold at the close price on day t+1. Second, we ignore the intraday stock trading. Actually, since day trading is not allowed in Chinese stock markets, there is almost no trading in which stocks are sold after buying them on the same trading day without the aid of short selling.

We calculate the gross return and abnormal return, respectively, to measure each investor's portfolio performance. The gross return of an investor *i*'s portfolio on day d (GR_{id}) is defined as

$$GR_{id} = \sum_{s=1}^{N_{i,d-1}} w_{i,s,d-1} * GR_{isd} \tag{4}$$

Here, $w_{i,s,d-1}$ is the weight of stock *s* in investor *i*'s portfolio on day *d-1*. The variable GR_{isd} is the return of stock *s* from day *d-1* to day *d* calculated using the close price after adjusting dividends and stock splits, and $N_{i,d-1}$ is the number of stocks held by investor i at day *d-1*.

The abnormal return in month t adjusted by contemporaneous market performance (CAR_{it}) is defined as

$$CAR_{it} = \sum_{d}^{M_t} (GR_{id} - r_{md}) \tag{5}$$

Here, GR_{id} and r_{md} are the gross return of investor *i*'s portfolio on day *d* and the value-weighted make return on day *d*, respectively. The variable M_t is the number of trading days in month *t*.

We also calculate performance using the characteristics-based benchmark portfolio. To construct the size/BM-based benchmark portfolio, all stocks are first independently sorted into five portfolios by size and BM at the end of month t-1. We then obtain 25 size/BM portfolios, and each stock is assigned to a size/BM portfolio as the size/BM-based benchmark portfolio at the beginning of each month. Similar to equation (5), the cumulative abnormal return adjusted by the contemporaneous characteristics-based portfolio is defined accordingly.

V. Data and Sample Statistics

1. Data sources

To explore investors' trading behaviors, we obtain proprietary data from a nationwide brokerage house in China. This unique dataset includes complete trade records of stocks for all clients in this particular brokerage house from January 2011 to March 2016. For each trade, we have information on the date, time, direction, size, encrypted account code, and investor type (institution or retail investor). The data contain 683,369 individual accounts and 756 institutional accounts. We analyze IPO events from April 2011 to December 2015 so that we are able to trace the trading behaviors of allocated versus non-allocated investors three months before and after each IPO lottery. IPO-related information and stock market data are all from China Stock Market & Accounting Research (CSMAR) database.

2. Identifying treated investors

Besides trading records, the proprietary data also record shares that investors obtain through non-trading ways, such as applying for IPO shares, stock splits, and so on, in the sample period. Retail investors who win the IPO lottery are allocated IPO shares and thus identified as "treated investors" in our randomized experiment.

Panel A of Table 1 summarizes the after-market performance of IPO events. We analyze 685 IPO events with an average winning probability of IPO lotteries of 1.47%. The average IPO discount measured using the first-day close price (the first-day close price/issue price - 1) is 24%. The 10^{th} percentile of the IPO discount is -4%, suggesting that there are about 70 IPO lotteries in which lottery winners lose money at the end of the first trading day. Because of the 44% upward price movement limits on the first trading day and the 23x PE cap since 2014, a more reasonable measure for the IPO price discount is calculated using the close price of the first day when stock prices are not subject to price movement limits after listing. On average, stock prices are not restricted by price movement limits until the sixth trading day after listing. The median cumulative return for IPO shares relative to the issue price is over 58%. Overall, while the success rate of the IPO lottery is very tiny, the relative return of winning IPO shares is really huge.

[Insert Table 1 around here]

Panel B of Table 1 describes the sample statistics of lottery winners. In our sample, 59,770 retail investors have been allocated IPO shares in at least one IPO event. In total, we have 99486 treated investor-event observations. Among treated investors, the median time for experiencing IPO lottery success is one. For each IPO event, most retail investors (over 90% of treated investors) are allocated 500 (1,000) IPO shares in the Shenzhen (Shanghai) Stock Exchange. The maximum number of IPO shares is 2,500, indicating that wealthy investors indeed spend a great deal of capital applying for IPO shares and have more than one allotment ticket as a lucky number in one IPO event. A typical lottery winner needs 11,200 yuan (the number of allocated IPO shares multiplied by the IPO issue price) to purchase IPO shares in the primary market, a number usually much smaller than the proceeds it takes to apply for IPO shares.

In Panel C of Table 1, we also look at the economic significance of gains from IPO shares by comparing with the market value of one's whole portfolio in stock markets before the IPO event. For a typical lottery winner, the IPO lottery gain is 8,600 yuan, which only accounts for 4% of the winner's total portfolio in stock markets. This result suggests that while the relative return of IPO shares is strikingly attractive, the IPO lottery gain compared with one's total portfolio is almost trivial.

In addition, we explore how long lottery winners would keep IPO shares. Interestingly, on average, we find that lottery winners sell 16% (25%) of allocated shares one (three) month(s) after the listing and that even one year after the listing, they still hold more than half of their allocated shares. Winners' reluctance to sell allocated IPO shares is possibly attributable to the endowment effect, consistent with the finding in Anagol, Balasubramaniam, and Ramadorai (2018) using Indian data.

3. Constructing control sample

To estimate the causal effect of IPO lottery success on subsequent trading behaviors, ideally, we should use as a control group those investors who also applied for IPO shares but were not allocated any shares because of the lottery result. However, our proprietary data are not able to identify unsuccessful applicants in the IPO lottery.

Directly taking all non-allocated investors as control groups is subject to sample selection biases because the decision of whether to apply for IPO shares is not random among investors. For example, investors who trade frequently are more likely to apply for IPO shares simply because they have more time to study stocks and thus become more familiar with IPO stocks. Alternatively, investors with stronger gambling desires are more likely to apply for IPO stocks because IPO lottery success enables them to make a huge profit in a short time. Therefore, lottery winners are probably substantially different from non-allocated investors who never apply for IPO shares. Moreover, the difference between these two types of investors is unobservable, which is not easy to solve by any matching approach relying on observable characteristics.

In this paper, we construct the control sample through the following steps. First, for each IPO lottery event, we select as the initial control groups those investors who are not allocated any IPO shares in three months before and after the focal IPO lottery event (called the "event period") but experience IPO lottery success outside the event period. Moreover, investors' gambling propensity may burst at any time for unobservable reasons, which could induce them to apply for IPO shares and trade lottery-like stocks. To mitigate these dynamic selection biases, we further require that the successful IPO lottery experience of control groups should fall within six months before and after the focal IPO event, but still be outside the event period (i.e., either from six months to four months before the focal IPO event or from four months to six months after the focal IPO event). Given that investors had successful IPO lottery experiences around the focal IPO event, they would probably have an interest in applying for IPO shares during that period. Thus, we could confine non-allocated investors to those that probably apply for but lose the focal IPO lottery because of bad luck; we call them the "filtered control group." Overall, all investors in the control groups not only applied for IPO shares but also had successful experiences, which helps us to mitigate selection biases arising from factors that determine whether to apply for IPO shares.[9]

Second, we match each treated investor to a control investor among filtered control groups using the propensity score matching (PSM) approach. The matching dimensions include portfolio size, portfolio turnover, and gambling propensity measured in different ways (see Section IV.2 for detailed definitions). We include portfolio size because the number of shares obtained from the IPO lottery is positively related to the size of the application, and thus larger investors are more likely to apply for

[9] Note that the way we construct the control sample is against finding any significant results from winning the IPO lottery because investors in the control group had a successful IPO lottery experience in earlier period, which could have exerted a long-term influence on their gambling propensity. In this sense, our approach offers a conservative estimation for the effect of IPO lottery success. In robustness checks (see Table A3), we use three alternative ways to construct the control sample, and the results are quite robust.

IPO shares. Given that investors who trade frequently are more active in stock markets and thus show greater interest in applying for IPO shares, we therefore include account turnover as an additional control. To study the effect of IPO lottery gains on investors' subsequent gambling behaviors, we require that the gambling propensity of control investors be comparable with that of treated investors before the treatment. The matching criterion is based on the average account characteristics in the three-month period prior to the IPO subscription.

In addition, to obtain a robust estimation of firms' lottery-like characteristics, we focus our analyses on stocks that have been listed for more than six months. To facilitate the before/after analyses, we further require that the number of non-IPO stocks that investors trade should be no less than three and that the number of months in which investors have trading records should be no less than two within three months both before and after the IPO month.

Finally, our sample includes 685 IPO lottery events, 59,770 treated investors, and 976,294 investor-month observations. Table 2 shows descriptive statistics of main variables in the final sample that includes both treated investors and matched control investors. The average of the account-level gambling propensity (*Lottery*) is 0.278.[10] The positive average value of gambling measures in our final sample suggests that investors taking part in the subscriptions of IPO shares exhibit greater gambling propensity than others. On average, investors in our final sample have a stock portfolio value of 118.97 thousand yuan ($e^{2.557}$-1) and a monthly portfolio turnover of 25.4%. The average market beta of investors' portfolios is close to 1. The average size beta and value beta of investors' portfolios are 0.400 and -0.199, respectively, indicating that investors in our sample prefer small growth firms.

[Insert Table 2 around here]

VI. Empirical Results

1. Univaraite test: Changes in gambling behaviors after winning IPO lotteries

We first gauge the effect of IPO lottery success on investors' gambling behaviors using a univariate test. In Table 3, we calculate the average gambling propensity within three months before (after) winning IPO lotteries for treated investors (i.e., lottery winners) and matched control investors, respectively. We measure investors' gambling propensity using the composite lottery index (*Lottery*). There is no significant difference in the gambling propensity between treated and matched control investors before the event. However, the gambling propensity of treated investors significantly increases after winning an IPO lottery, which is much larger than the contemporaneous change of matched control investors. The difference-in-difference change of *Lottery* is 0.051, which is significant at the 1% level, indicating that IPO lottery success induces lottery winners to substantially shift their

[10] One thing worth noting is that while account-level gambling measures are standardized each month, the average values of these measures are greater than zero in our final sample. This is because we first standardize account-level gambling measures using all investors that are available in our brokerage data and then based on standardized gambling measures run the PSM procedure to match control investors.

portfolios toward lottery-like stocks relative to matched control investors. Regarding the economic significance, the difference-in-difference change of *Lottery* is roughly 18.3% (=0.051/0.278) of its mean value prior to the event and 5.8% (=0.051/0.885) of its standard deviation. Overall, these results suggest that lottery-like cues exert considerable influence on investors' gambling behaviors in stock markets.

[Insert Table 3 around here]

To exactly time the changes in investors' stock preferences, Figure 1 plots the dynamics of average gambling propensity for treated and matched control investors from 60 days before through 60 days after winning IPO shares. First, we calculate the daily-level gambling propensity for each account following similar steps in Section IV.2. Second, for each allocated investor of IPO stock *i*, we exploit propensity score matching procedures to find one for one matched investor. The matching criterion includes account-level gambling propensity measures over prior 10/20/40/60 days and the number of trading days over prior 60 days. Third, we calculate the average gambling propensity on each day from 60 days before through 60 days after winning IPO shares for treated and matched control investors, respectively. We require the number trading days of each investor in our sample during the 60 days before (after) winning IPO shares should be greater than five.

The figure shows that, prior to the event day, there is no significant difference in gambling propensity between treated investors and matched control investors in each month, consistent with the assumption of a "parallel trend." Once investors win an IPO lottery, their gambling propensity significantly increases, and the upward trend continues until 30 days after the event. The gambling propensity of lottery winners becomes significantly higher than that of matched control investors after winning an IPO lottery. Moreover, while investors' gambling propensity varies across time, the difference in gambling propensity between lottery winners and matched control investors does not reverse in subsequent 60 days.

[Insert Figure 1 around here]

2. Baseline regressions

In Table 4, we estimate the difference-in-difference effect of exposure to lottery-like cues on subsequent gambling propensity using regressions with various control variables. Compared with the analyses in Table 3, in columns (1), we include IPO event fixed effects in order to ensure that we only exploit the variation within each randomized allocation to estimate the causal impact of IPO lottery success on investors' gambling propensity. The coefficient of *Treat*Post* is essentially a weighted average of the treatment effects of all IPO lotteries. We exploit standard errors clustered at the account level to calculate *t-statistics*. The coefficient of *Treat* is insignificant, confirming the efficiency of our matching procedure in constructing control groups. The coefficient of *Post* is positive, suggesting that the preference for lottery-like stocks of matched control investors in the final sample also increases mildly during the sample period. Most importantly, the coefficients of *Treat*Post* are both positively significant, again confirming that compared with matched control investors, lottery winners significantly shift their portfolios toward lottery-like stocks after the event. Moreover, the magnitude of coefficients of the interaction item in columns (1) is comparable with what we calculate in Table 3.

[Insert Table 4 around here]

While the difference-in-difference estimation should not be affected by time-invariant factors (e.g., investor demographic information), we nonetheless include investor fixed effects to increase the precision of our estimation in column (2). After controlling for the investor fixed effect, the variable *Treat* is omitted because it is absorbed by the fixed effect. In column (3), we further add investor portfolio size at the beginning of each month and monthly portfolio turnover to control for the influence of time-varying investor characteristics. The coefficient of *Treat*Post* is 0.0233, significant at the 1% level, though the magnitude decreases a bit. These results suggest that our estimated effect is not fully captured by time-invariant or time-varying investor characteristics.

In addition, the coefficient of *Ln(InvSize)* is positively significant even controlling for investor fixed effects, suggesting that investors are more likely to undertake lottery-like investment when investors make profits or increase their investment in stock markets, possibly because of their greater willingness to take on risk. The coefficient of *Ln(InvTov)* is also positively significant, implying that investors with higher portfolio turnover also prefer lottery-like investments.

To mitigate the influence of particular periods (e.g., stock market boom and bust periods) on the estimation, we further include calendar month fixed effects or event month fixed effects in the regressions. When additionally controlling for event month fixed effects, the variables *Treat* and *Post* are both omitted. The results show that all coefficients of the interaction items are positively significant in columns (4) and (5) and that the magnitudes of these coefficients are comparable with those in column (3), suggesting that time variation does not account for our estimated effect.

Given that the trading behaviors of different investors at a given time are likely to be highly correlated with each other because of investor sentiment or common demand shocks, we also calculate *t-statistics* using standard errors clustered by both account and calendar month as robustness checks. The results (see Table A2) show that the coefficients of interaction items are still highly significant.

To mitigate the dynamic sample selection biases, we require that control investors are not allocated IPO shares within the event periods but have successful IPO lottery experiences around the event period. The way we construct control samples essentially offers a conservative estimation for the effect of IPO lottery success on investors' gambling behaviors. We also exploit alternative ways to construct control samples to explore the effect of IPO lottery success. The results are displayed in Table A3. In columns (1) and (2), we include all investors who are not allocated IPO shares within three months before and after the focal IPO event in the "filtered control group" and then exploit the PSM procedure to match control investors. Taking the results controlling for both investor and time fixed effects, for example, the coefficient of interaction item is 0.0428 (in column (1)), significant at the 1%

level, which is more than 1.5 times larger than the similar estimate of our baseline results (0.233, in column (3) of Table 4), confirming that our estimation in Table 4 is conservative in gauging the influence of lottery-like cues on investors' behaviors.

We then add more restrictions to the "filtered control group". In column (3) and (4), we require that investors in the "filtered control group" should have at least one successful IPO lottery experience three months before or after the event month. Note that in the baseline results, we additionally require that the successful lottery experience of control investors should be around the focal IPO event to mitigate the dynamic sample selection biases. The results are quite similar to what find obtain in column (1) and (2) of Table A2.

In column (5) and (6), we require that investors in the "filtered control group" should have at least one successful IPO allotment three months before the event month. In this case, all control investors had successful IPO lottery experiences. If the successful lottery experience exerted a long-run influence on investors' gambling propensity, the way we construct the control sample is against any significant finding from the focal IPO lottery event. The results show that the coefficient of "*Treat*Post*" in column (6) is 0.0324, which is smaller than the coefficients in columns (1) and (3) but still larger than the estimate in our baseline results. At any rate, the significant increases in investors' gambling propensity after winning an IPO lottery are not affected by the way we construct the control sample.

Overall, the regression results indicate that compared with matched control investors, the gambling propensity of lottery winners significantly increases over the subsequent three months even controlling for dynamic investor characteristics as well as account and time fixed effects. The results are quite robust to different types of standard errors and to alternative ways of constructing control samples.

3. The moderating effect of cue salience

In this section, we further examine whether the effect induced by randomized exposure to lottery-like cues on subsequent gambling propensity varies with the salience of the cue. In Section III.2, we argue that IPO lottery success activates lottery-like features in memory and increases one's ability to recall tail returns when making investment decisions so that lottery winners exhibit an increased preference toward lottery-like stocks. We argue that the associative activation in memory should increase with the salience of external cues. That is, more salient lottery-like cues are associated with stronger activation effects. Therefore, we conjecture that increases in gambling propensity after winning an IPO lottery will be more pronounced when the salience of the IPO lottery success increases.

In the context of an IPO lottery, we argue that the salience of IPO lottery success is at least closely related to the following two factors. First, the salience is negatively related to the average winning rate of an IPO lottery. Investors are more likely to pay attention to a low-probability scenario in subsequent decision making after winning IPO lotteries with a lower average winning rate. Second, the salience is positively related to the issue-price discount. Lottery winners who win IPO shares at a greater discount would have a deeper impression of extremely positive returns in memory. Therefore, winning an IPO allotment that has a lower success rate or a larger price rise in the aftermarket (i.e., a higher price discount) makes treated investors more likely to be influenced by lottery-like stimuli.

In columns (1) and (2) of Table 5, we explore whether the effect of IPO lottery success on investors' gambling propensity varies with the average winning rate of IPO lotteries. The regressions in this table are confined to the sample of lottery winners. The dependent variable is investors' gambling propensity in month *t* measured by *Lottery*. The variable *Post* is a dummy variable that equals one (zero) for months after (before) winning IPO shares. For each IPO stock, *Winning Rate*, the average probability of winning IPO shares, equals the number of shares issued through an online IPO lottery divided by the total number of subscriptions. We argue that the salience of IPO lottery success decreases with the average winning rate of IPO lotteries. In column (1), we include investor and calendar month fixed effects in the regressions. The coefficients of the interaction item are of great interest. The coefficient of "*Post*Winning Rate*" is -0.00177, significant at the 10% level.[11] In column (2), we add IPO stock fixed effects, and thus the variable "*Winning Rate*" is omitted. The coefficients of the interaction item remain negatively significant. These results suggest that increases in lottery winners' gambling propensity are negatively related to the winning rate of IPO lotteries (noting that an IPO lottery success with a lower average winning rate implies a more salient lottery cue).

[Insert Table 5 around here]

In columns (3) and (4) of Table 5, we explore whether the effect of IPO lottery success on investors' gambling propensity varies with the IPO issue-price discount. The model specifications are similar to those in Table 5. We exploit the issue-price discount to measure the salience of IPO lottery success. The IPO issue-price discount (*Discount*) is calculated using formula (6):

$$Discount = \frac{Close\ \ price - IPO\ \ issue\ \ price}{IPO\ \ issue\ \ price} \tag{6}$$

Here, *Close price* refers to the closing price of the IPO stock on the first day that is not subject to upward/downward price limits after going public, and *IPO issue price* is the issue price of IPO shares determined by underwriters. We argue that the salience of IPO lottery success also increases with the after-market performance of IPO shares. The coefficients of the interaction item (*Post*Discount*) are all positive and significant at the 1% level, suggesting that the effect of IPO lottery success on investors' gambling propensity is more pronounced when an IPO firm has a larger issue-price discount.

Overall, our results in this section indicate that the salience of lottery-like cues accounts for the cross-sectional variations of changes in lottery winners' gambling behaviors around an IPO lottery. In addition, one might argue that either the winning rate of an IPO lottery or the issue-price discount could be associated with the wealth shock that investors experience from the IPO lottery success. In

[11] In untabulated results, we find that the coefficient of "*Post*Winning Rate*" is significant at the 1% level, when measuring investors' gambling propensity using *MAX*.

untabulated results, we show that these cross-sectional variations, along with the salience of IPO lottery success, still hold when controlling for the impact of the investor-level size of IPO gains, suggesting that changes in investors' wealth can hardly explain variations in our findings along these dimensions.

4. Portfolio performance

In this section, we evaluate changes in investors' non-IPO portfolio performance before and after the IPO lottery success by comparing with matched control investors. This exercise sheds light on the economic consequences of changes in trading behaviors influenced by external lottery-like cues.

Following Barber and Odean (2000), we calculate the non-IPO portfolio performance for lottery winners and matched control investors, respectively, and test their differences before and after the IPO lottery event. Section IV.4 introduces the detailed calculation method of investor performance. Panel A of Table 6 reports the average monthly raw return for treated investors and matched control investors in different periods. In the pre-three-month period, treated investors perform better than matched control investors.[12] However, in the post-three-month period, the investment performance of treated investors is 0.17% lower than that of matched control investors per month. The difference-in-difference change in treated investors' raw performance is -0.38% per month, implying that the investment performance of lottery winners decreases significantly after winning IPO lotteries.

[Insert Table 6 around here]

We also measure investment performance using both the market-adjusted return and the characteristic-adjusted return. We introduce the detailed procedures to calculate these returns in Section IV.4. Panel B of Table 6 displays the results of the market-adjusted return. Consistent with the results of the raw return, the investment performance of lottery winners deteriorates relative to matched control investors after winning IPO lotteries. The difference-in-difference estimate for the underperformance using the market-adjusted return is -0.31% per month. We also adjust the raw return using the corresponding size/BM portfolio (5x5). The results are reported in Panel C of Table 6. Qualitatively, the results are similar to those in Panels A and B. Interestingly, the underperformance of lottery winners when measured with the size/BM-adjusted return shrinks to -0.26% per month (i.e., a one-third reduction compared with the case using the raw return), implying that the underperformance of lottery winners after winning an IPO lottery is partly attributable to changes in the styles of stock selection.

Table 7 reports "difference-in-difference" estimates for the effect of IPO lottery success on investors' non-IPO performance using regressions with various control variables. The dependent variable is investor performance in month *t*, measured using the raw return (RR), market-adjusted return (MAR), and size/BM-adjusted return (SBAR), respectively. We include IPO event fixed effects,

[12] Note that matched control investors here are the same as what we constructed in Table 3. Investor performance is not included as a criterion in the PSM procedure.

investor fixed effects, and calendar month fixed effects as well as dynamic investor portfolio characteristics in all regressions. Of interest is the coefficient of the interaction item. The coefficients of "*Treat*Post*" are all negative and significant at the 1% level, indicating that the adverse consequence of winning IPO lotteries on lottery winners' non-IPO portfolio performance still holds when controlling for dynamic investor characteristics as well as account and time fixed effects. Moreover, the coefficient of the interaction item when estimated using characteristic-adjusted returns (in column (3)) is smaller in absolute magnitude than that of the raw return (in column (1)), again confirming that changes in the preference for stock characteristics after winning an IPO lottery drive lottery winners' underperformance.

[Insert Table 7 around here]

In Table 8, we exploit a direct way to examine the link between changes in lottery winners' gambling propensity and their performance changes around the IPO lottery success.[13] We first estimate the "difference-in-difference" change in both gambling propensity and investment performance for each treated investor and then run cross-sectional regressions to examine whether changes in investment performance are significantly associated with changes in gambling propensity across treated investors.

For each treated investor, DID^{VAR} denotes the "difference-in-difference" change of *VAR* relative to his/her matched control investor, which is identified by estimating the coefficient of *Treat X Post* using formula (7):

$$VAR = b_0 + b_1 Treat + b_2 Post + b_3 Treat * Post + e \tag{7}$$

VAR indicates variables exploited in the regressions, including investor-level gambling propensity (*Lottery*), investor portfolio turnover (*Ln(InvTov)*), and investment performance (raw return, market-adjusted return, and size/BM-adjusted return). The variable *Treat* is a dummy variable that equals one (zero) for treated (control) investors, and *Post* is a dummy variable that equals one (zero) for months after (before) winning IPO shares.

Figure 2 offers a preliminary analysis on the association. We first sort treated investors into five groups based on their "difference-in-difference" changes in gambling propensity ($DID^{Lottery}$) and then plot the average "difference-in-difference" change of investment performance in each group. Investor performance is measured with raw return, CAPM alpha, and FF3F alpha, respectively. The results show that treated investors who shift their portfolio more toward lottery-like stocks after winning an IPO lottery exhibit greater investment performance deterioration in subsequent months.

[Insert Figure 2 around here]

[13] Frydman and Wang (2020) estimate an individual-level measure for the influence of salience shocks on one's disposition effect for each treated investor and construct individual-level measures for one's tendency of salience thinking from their trading histories. Then, they study the link between these two measures to explore the underlying mechanism in changes in investors' behaviors. Our exercise here is similar in spirit.

Table 8 reports the cross-sectional regression results. The coefficients of $DID^{Lottery}$ are all negatively significant at a 1% level, implying that the decreases in investors' non-IPO portfolio performance are significantly associated with increases in their gambling propensity. Overall, our findings suggest that gambling behaviors induced by external lottery-like cues are costly for retail investors, exacerbating their underperformance.

[Insert Table 8 around here]

In addition, Anagol, Balasubramaniam, and Ramadorai (2019) and Gao, Shi, and Zhao (2018) document that IPO lottery winners substantially increase non-IPO portfolio turnover relative to IPO lottery losers in India and China, respectively. Excessive trading in stock markets is hazardous to one's wealth (Barber and Odean, 2000). Thus, the underperformance of lottery winners after winning IPO lotteries could be driven by overtrading rather than gambling behaviors. To tease out the influence of this alternative channel, we control for the "difference-in-difference" changes in portfolio turnover ($DID^{ln(InvTov)}$) in all regressions. The coefficients of $DID^{Lottery}$ are all still negatively significant, indicating that it is the increased gambling behaviors rather than overtrading that lead to wealth losses. Particularly, the coefficient of $DID^{ln(InvTov)}$ is significantly positive when controlling for changes in gambling propensity, inconsistent with the argument that more trading would lead to worse performance.[14] Thus, one possible explanation is that the influence of overtrading on performance could be partially due to the effect of changes in investment styles after winning an IPO lottery.

Lastly, owing to the underperformance after winning an IPO lottery, rational learning about investors' ability or stock return dynamics is unlikely to explain our findings. In addition, given that these lottery-like stocks are riskier on average, IPO winners are taking more risks but experiencing lower returns, which is especially hard to reconcile with a purely rational explanation.

VII. Discussions on alternative stories

Although the trading behavior we have documented is hard to reconcile under a purely rational framework, there are still alternative channels to explore in accounting for the associated changes in investors' gambling propensity after winning an IPO lottery. In this section, we provide further evidence and discussions to mitigate the concern that these alternative explanations drive our results.

1. House money effect

One important alternative explanation is the house money effect (e.g., Thaler and Johnson, 1990), which argues that investors create a separate "mental account" for their winnings in the stock market and that they are willing to increase their level of risk taking with these winnings. Thus, increased

[14] Gao, Shi, and Zhao (2018) also document that lottery winners lose more money subsequent to winning IPO shares relative to lottery losers. However, they do not directly show that underperformance is attributed to increases in trading frequency. In untabulated results, we find that, if we do not control for the effect of increased demand for lottery-like stocks, the coefficient on $DID^{ln(InvTov)}$ is indeed negative. That is, for investors with more increases in turnover, their future underperformance is more pronounced.

gambling behaviors after experiencing IPO lottery gains could result from investors' greater willingness to take on risk, as opposed to the priming effect of lottery-like cues.

The main point of the house money effect is that investors would create a separate "mental account" for the money they made in the stock market and that they probably exhibit different risk preferences or investment styles with these proceeds. According to the house money effect, there should be no significant difference between the effect of money that is made from IPO shares and that of non-IPO portfolios on subsequent trading behaviors.

To empirically examine this conjecture, Table 9 directly compares the effect of gains from IPO lotteries on investors' subsequent gambling propensity with that of prior performance of non-IPO stocks by estimating the following regression equation:

$$Gambling_{i,t} = b_0 + b_1 IPO\ \ Profit_{i,[t-3,t-1]} + b_2 Performance_{i,[t-3,t-1]} + Controls + e_{i,t} \qquad (8)$$

Here, *i* denotes investor and *t* denotes calendar month. We measure investors' gambling propensity using *Lottery*. The variable *IPO Profit* is gains from winning IPO shares within the past three months divided by one's portfolio value. Specifically, for IPO shares that have been sold in the past three months, we calculate the realized profit according to their sale records; for IPO shares that are still kept in one's portfolio, we calculate their paper gain/loss until the end of month t-1. The variable *IPO Profit* is calculated by aggregating realized gains and paper gains on one's winning IPO shares. If an investor wins IPO shares multiple times in the past three months, we accumulate the investor's gains from each IPO stock to calculate *IPO Profit*. We follow Barber and Odean (2000) to calculate trading performance among non-IPO stocks of investor *i* within the past three months (*Performance*). In Panels A and B, we run the regressions among treated investors and all investors, respectively.

[Insert Table 9 around here]

The coefficient of *IPO Profit* is positively significant, confirming our prior finding that investors exhibit an increased gambling propensity after winning IPO lotteries. The coefficient of *Performance* is also positively significant. This result is consistent with the house money effect that investors have an increasing gambling propensity after they made money in stock markets. While prior gains in stock markets have a positive influence on one's gambling propensity, its magnitude is much smaller than that of profits from IPO shares. This contrast is more pronounced when controlling for investor fixed effects. For example, the coefficient of *IPO Profit* in column (2) of Panel A is 1.535, which is more than seven times larger than that of *Performance* (0.192). The impact of gains from IPO shares is still almost three times larger than that of general prior gains even after controlling for investor and calendar month fixed effects (see column (3) of Panel A). Overall, while we find supporting evidence for the house money effect in our sample, these results, as a whole, indicate that the effect of winning IPO lotteries on investors' gambling propensity is hardly justified by the house money effect.[15]

[15] In untabulated analyses, we repeat the exercise in Table 10 by replacing the dependent variable, gambling, with

2. Wealth effect

A second potential explanation for changes in investors' gambling propensity after winning an IPO lottery is the wealth effect, which states that winning IPO shares increases one's wealth and thus one's risk-bearing capacity. In other words, the increased gambling behaviors could be the outcome of increases in risk tolerance induced by the wealth effect. However, on the theoretical side, wealth could be positively or negatively correlated with risk preference, depending on the assumption of a standard utility function.[16] Thus, from an ex ante perspective, it is unclear how the wealth gain from winning the IPO allocation would influence individuals' subsequent trading behavior.

Based on the evidence we obtain, it is also difficult to interpret our finding as arising from the wealth effect. First, the average gain from an IPO lottery, 5,100 yuan, is quite small relative to average account assets of 118,700 yuan. This fact makes it unlikely that winning the IPO lottery is somehow relieving a wealth constraint that causes a change in behavior across lottery winners and losers.

Second, we find that even for investors with an average portfolio size in excess of 1 million yuan, IPO lottery success continues to produce economically and statistically significant effects on their gambling propensity. Specifically, we first classify investors into the "Large" ("Small & Medium") group when their average portfolio value during the three months before the event month market is larger (smaller) than 1 million yuan. We then rerun the baseline regressions from Table 4 in each group. We control for IPO stock fixed effects, account fixed effects, and calendar month fixed effects, as well as dynamic investor characteristics in all regressions.

The results are reported in Table 10. Regardless of investors' portfolio size, the coefficients of the interaction item (*Treat*Post*) are all positively significant. Particularly, even for investors with average portfolio sizes in excess of 1 million yuan, the gains from IPO shares are relatively small. However, the effect of winning an IPO lottery on subsequent gambling propensity continues to be statistically and economically large. Interestingly, our finding actually shows that the effect of a successful IPO lottery experience appears to be stronger for larger accounts and that the difference is quite large. The coefficient of *Treat*Post* is 0.0528 among large investors, which is more than twice that among small and medium investors (0.0205). This finding is contrary to the prediction of the wealth effect.

[Insert Table 11 around here]

Lastly, the pure wealth effect is hard to reconcile with the subsequent underperformance of the IPO winners. If the IPO winners are more risk tolerant, and thus taking on more risk, the rational risk-

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portfolio turnover, and thus we compare the effect of gains from IPO lotteries on investors' subsequent portfolio turnover with that of prior performance of non-IPO stocks. While the results are somewhat sensitive to model specifications, the key message we obtain is that the influence of IPO profit on trading turnover is not significantly different from that of prior non-IPO performance, particularly after controlling for account and time fixed effects. Thus, IPO profits have a special effect on demand for lottery-like stocks, but not on general portfolio turnover, again supporting the role of priming.

[16] Recent empirical literature also challenges the relation between wealth and risk preference. Brunnermeier and Nagel (2008) conclude that wealth fluctuations have only minor effects on risk tolerance.

return trade-off implies that their subsequent performance should be better than that of the IPO losers.

3. Overconfidence

A third possibility in explaining changes in investor behavior is related to investors' overconfidence. Anagol, Balasubramaniam, and Ramadorai (2019) argue that lottery winners learn from the experience of IPO lottery activities and disproportionally attribute the random success to their own ability, thus increasing their overconfidence in subsequent decision making. According to their arguments, increased overconfidence may also fuel gambling activities in stock markets after winning an IPO lottery, possibly because overconfident investors may overestimate the probability of the upside potential of lottery-like stocks.

First, while increased overconfidence would increase lottery winners' propensity to trade, predicting that lottery winners have an increased likelihood of trading lottery-like stocks following the random shock seems to require additional assumptions. Second, overconfidence due to biased learning also occurs after making profits from non-IPO stocks. Given this, the results in Table 10 indicate that while overconfidence could lead to increased gambling propensity, the magnitude of the effect associated with winning IPO shares is hardly justified by the biased-learning hypothesis.

4. Feeling lucky

A fourth possibility is that the psychology of "feeling lucky" may drive our results. This possibility argues that lottery winners may believe that they are experiencing a period of unusual luck in a manner that is reminiscent of the "hot hand fallacy" effect (e.g., Gilovich, Vallone, and Tversky, 1985). In this case, lottery winners may simply believe that the probability of experiencing future high returns should be greater following a random lucky experience such as winning an IPO lottery and thus exhibit a greater preference toward lottery-like stocks.

If the "feeling lucky" story drives our results, we expect that lottery winners would also increase their overall investment in stock markets because investors who feel extremely lucky probably have an increased risk appetite. In Table 11, we explore the effect of IPO lottery success on overall investment in stock markets using the "difference-in-difference" approach similar to our baseline regressions. We exploit net buy to approximate investors' new investment into stock markets. Specifically, the dependent variable is an investor's net buy (i.e., dollar purchase minus dollar sale) in month t divided by total trading volume in this month (or portfolio value at the end of month t-1). The results show that, the coefficients of the interaction item (*Treat*Post*) are all negative and significant at 1% level in most settings (except Column (4) when controlling for calendar month fixed effects), suggesting that lottery winners are prone to reduce rather than increase their investment in stock markets. Overall, our evidence at least shows that lottery winners do not increase their overall allocation to stocks, which is not consistent with the prediction of the "feeling lucky" explanation.

[Insert Table 11 around here]

Moreover, the “hot hand fallacy” effect, traditionally accounts for cognitive biases for the same activity. Our evidence shows that success in an IPO lottery breeds the decision to invest in other lottery-like stocks, revealing the association of investors’ propensity to participate in different investment activities. Thus, beliefs about luck alone hardly account for our finding; it also has to be accompanied by a shift in investors’ attention toward lottery-like characteristics. More important, the hot hand fallacy usually holds for activities involving skills such as stock picking or basketball shooting. For purely random activities, such as rolling dice, investors typically hold to the gambler’s fallacy, which is the belief that after a series of “big,” the next one should be “small.” Thus, the gambler’s fallacy implies that after good luck, investors might expect bad luck in the future since luck is purely random. Actually, the gambler’s fallacy can be used to explain the hot hand effect (see, e.g., Rabin and Vayanos (2010)). If investors hold to the gambler’s fallacy for this purely random activity, they should invest less in lottery-like stocks after winning an IPO lottery.

In addition, we explore how prior IPO lottery winning experiences influence their subsequent gambling propensity. The “feeling lucky” explanation may predict that the winner should feel particularly lucky after experiencing IPO lottery success more than one time, and thus invest more in lottery-like stocks. However, our untabulated results show that increases in gambling propensity are more pronounced among investors who have limited successful experiences in IPO lotteries, indicating that the effect of IPO lottery success decays as one’s related experiences increase. This finding contradicts the “feeling lucky” explanation. This finding is also consistent with Anagol, Balasubramaniam, and Ramadorai’s (2019) finding that investors who have received multiple past IPO allocations show smaller and substantially increase portfolio trading volume in non-IPO stocks relative to one time IPO lottery winners.

VIII. Further Analyses

This section further explores investor characteristics contributing to the heterogeneity of the priming effect and conditions under which the tendency to gamble in stock markets after winning IPO lotteries is intensified or attenuated. The cross-sectional patterns of priming effect not only motivate theorists to incorporate the investor heterogeneity in their models, but also have important welfare and regulatory implications.

1. Trading experiences

A large strand of literature shows that trading experiences help to eliminate or reduce behavioral biases. For example, List (2003, 2011) provides experimental evidence that the endowment effect can be eliminated as market interactions increase, suggesting that experiences can lead market participants to behave in a rational way. Several studies using individual account-level trading data (e.g., Dhar and Zhu, 2006; Feng and Seasholes, 2005) document a negative relationship between investors’ trading experiences and the magnitude of disposition effect. Seru, Shumway and Stoffman (2010) further attribute the attenuation of disposition effect as trading experiences increase to the “learning by trading” effect. Similarly, investors who entered the stock market earlier may have a better appreciation of the rational investment principle that renders their stock preferences less susceptible to random events in one's memory. Thus, we expect that increases in gambling propensity due to priming effect should be smaller for investors with richer trading experiences.

In this section, we explore whether trading experiences attenuate the magnitude of priming effect. We measure trading experiences with the length of time investors that spend in stock markets. Specifically, *Account Age* is the cumulative number of months from one's first trading month in our sample to the month winning IPO shares. *Experienced* is a dummy variable, which equals one if the account has over two years' trading records upon winning IPO shares and zero otherwise. Among treated investors, we estimate the equation (9) and equation (10), respectively. IPO lottery fixed effects, account fixed effects, and calendar month fixed effects are all included. The coefficients of the interaction items capture the influence of trading experiences.

$$Gambling_{ijt} = a_0 + a_1 Post_{jt} + a_2 Post_{jt} * Account\ \ Age_i + Controls + e_{ijt} \tag{9}$$

$$Gambling_{ijt} = b_0 + b_1 Post_{jt} + b_2 Post_{it} * Experienced_i + Controls + e_{ijt} \tag{10}$$

Here i, j, and t indicates investor, IPO event, and calendar month, respectively.

Table 12 displays the results. The coefficients of interaction items are all negatively significant in different specifications, suggesting that experienced investors' trading behaviors are less likely to be affected by external lottery cues. In untabulated results, we find that increases in gambling propensity for "rookie" lottery winners (i.e. trading history is no more than two years) are twice larger than that of experienced ones. These findings indicate that experienced retail investors learn to mitigate the influence of priming effect, and that financial advisors may focus on helping early-stage retail investors become aware of the influence and contain their irrationality.

[Insert Table 12 about here]

2. Portfolio performance

An, Engelberg, Henriksson, Wang, and Williams (2019) document that prior portfolio performance influences investors' subsequent trading behaviors. They find that investors are more likely to sell a losing stock when their portfolio is at a gain rather than at a loss. Inspired by their studies, we conjecture that investors' prior portfolio performance will influence their responses to IPO lottery success. Investors with portfolio gains are likely to increase their gambling propensity when exposed to external lottery-like stimuli, possibly because portfolio gains make it easier to evoke their memory of the upside potential of lottery-like stocks. On the contrary, investors with portfolio losses are likely to stay away from volatile stocks in order to lock in the profit from IPO shares and reduce the pain of portfolio losses. Therefore, we expect that, compared with those with portfolio losses, investors with portfolio gains are more likely to increase their gambling propensity after winning an

IPO lottery. That is, the priming effect of IPO lottery winning is influenced by the outside environment, such as overall portfolio performance.

In this section, we divide treated investors into subgroups by their portfolio performance over the three-month period before winning an IPO lottery. Investors with losses (gains) are equally divided into two subgroups and labeled "Large loss" ("Large Gain") and "Small Loss" (Small Gain), respectively. We measure investors' portfolio performance using raw returns (size/BM-adjusted returns). In each subgroup, we then estimate the following regression:

$$Gambling_{ijt} = a_0 + a_1 Post_{jt} + Controls + e_{ijt} \quad (11)$$

We then compare changes in gambling propensity around the IPO lottery success (i.e., the coefficient of *Post*) across different groups. We include investor fixed effects and investor characteristics in all regressions.

The results are reported in Table 13. For investors with a large gain, the coefficient of *Post* is positively significant (0.0367, in column (4) of Panel A), suggesting that investors increase their gambling propensity after winning an IPO lottery. For investors with a large loss, the coefficient of *Post* is negatively significant (-0.0431, in column (1) of Panel A), suggesting that investors move away from lottery-like stocks in subsequent trading. The contrast in patterns between investors with portfolio gains and portfolio losses is more robust when measuring performance using size/BM-adjusted returns. Overall, our results show that investors with large losses (gains) are least (most) likely to shift their portfolio toward lottery-like stocks after winning IPO lotteries. These findings confirm our conjecture that prior portfolio performance is an important factor that influences investors' responses to external stimuli.

[Insert Table 13 around here]

IX. Conclusions

This paper explores how external cues influence investors' preferences and decision making in stock markets by exploiting randomized distributions of IPO shares as natural experiments. We hypothesize that successful lottery-like experiences increase investors' gambling preferences by increasing the accessibility of tail returns. We indeed find that lottery winners substantially shift their non-IPO portfolios toward lottery-like stocks subsequent to the distribution. Winning an IPO security that has a lower success rate or a larger price rise in the aftermarket (i.e., a higher price discount) makes treated investors more likely to be influenced by lottery-like stimuli.

Moreover, lottery winners experience a decrease in their overall portfolio return by more than 1% within the three months subsequent to the distribution relative to matched control investors. The decreases in investors' non-IPO portfolio performance are significantly associated with increases in their gambling propensity. Therefore, gambling behaviors induced by external lottery-type cues are costly for retail investors, exacerbating their underperformance. We further show that our findings are not explained by the house money effect or the wealth effect.

This paper explores the effect of naturalistic primes on subsequent financial decisions. We show that randomized IPO lottery success induces investors to overweight tail returns and invest more in lottery-like stocks. Our results suggest that the priming effect and associative activation are important mechanisms that influence investors' decisions in financial markets. Our study also responds to replication crises of experimental evidence on behavioral priming by highlighting the importance of the priming effect in the real world based on a large sample of real transaction data.

Very little work in finance explores the underlying psychology of overweighting tail returns. Barberis (2013) proposes a possible explanation based on availability heuristics in a review paper. We provide causal evidence that the accessibility of tail returns at least partially accounts for investors' gambling preference in stock markets. In addition, our findings also suggest that participation in IPO lotteries has a negative spillover effect on retail investors' welfare through the trading of non-IPO stocks, which sheds light on the controversy of the allocation proportion of IPO issuance between institutional investors and retail investors.

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Figure 1 The dynamics of gambling behaviors around IPO lottery events

This plots the daily dynamics of average gambling propensity for treated and matched control investors from 60 days before through 60 days after winning IPO shares. First, we calculate the daily-level gambling propensity for each account following similar steps in Section IV.2. Second, for each allocated investor of IPO stock *i*, we exploit propensity score matching procedures to find one for one matched investor. The matching criterion includes account-level gambling propensity measures over prior 10/20/40/60 days and the number of trading days over prior 60 days. Third, we calculate the average gambling propensity on each day from 60 days before through 60 days after winning IPO shares for treated and matched control investors, respectively. We require the number trading days of each investor in our sample during the 60 days before (after) winning IPO shares should be greater than five.

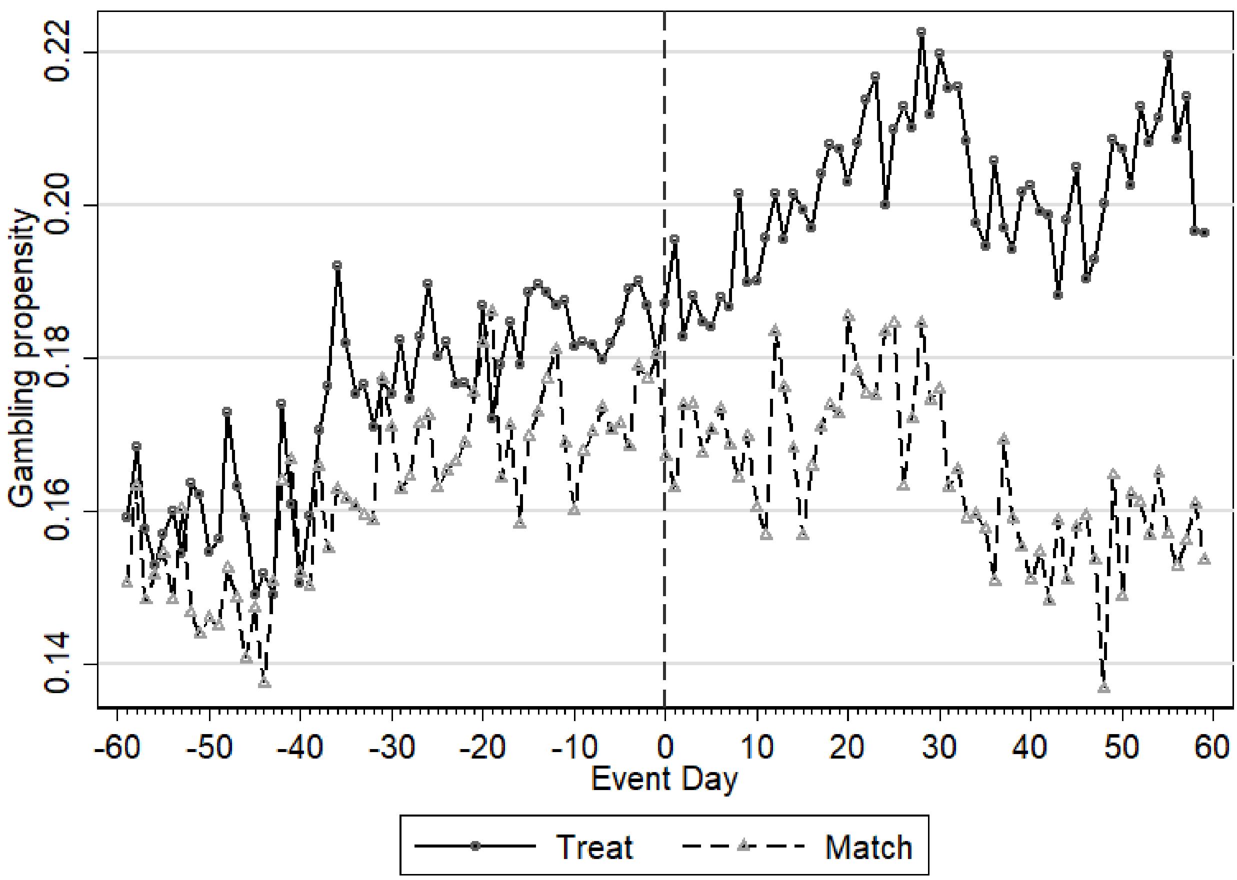
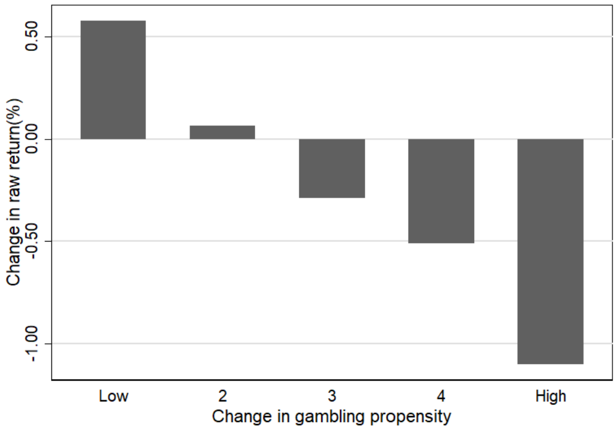
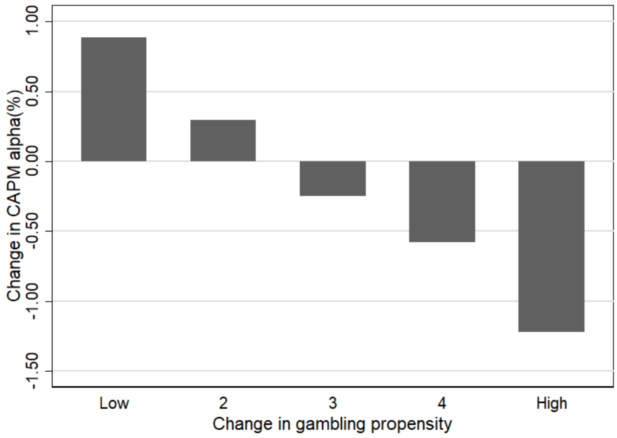


Figure 2 Changes in gambling behaviors and performance changes

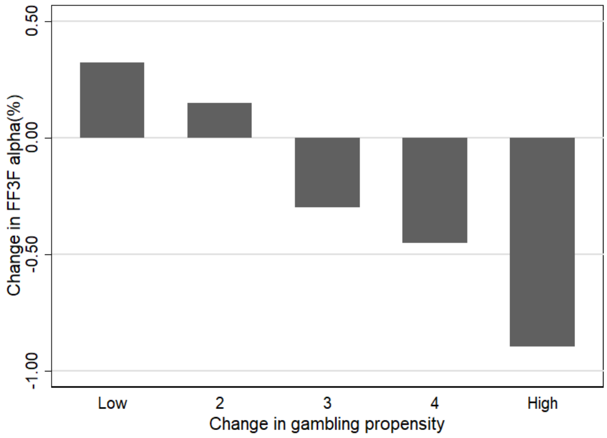
In Figure 2, we first sort treated investors into five groups based on their "difference-in-difference" changes in gambling propensity ($DID^{Lottery}$) and then plot the average "difference-in-difference" change of investment performance in each group. Investor performance is measured with raw return, CAPM alpha, and FF3F alpha, respectively.



(a)



(b)



(c)

Table 1 Summary Statistics

Panel A summarizes stock-level information of IPO events. Panel B displays investor-level information of winning IPO shares. Panel C calculates lottery winners' cumulative profit from IPO shares until the end of the first month after winning shares.

Variables	N	Mean	Sd	Min	p25	p50	p75	Max
Panel A: IPO information								
Avg. probability of winning IPO shares	685	1.47	3.18	0.21	0.45	0.73	1.44	12.1
IPO first-day discount	685	0.24	0.28	-0.14	0.10	0.20	0.32	0.97
# days hitting price limits	685	5.35	6.27	1	1	1	9	25
Cumulative returns from first IPO day to the first day not hitting the upper price limits	685	1.65	2.73	-0.1	0.13	0.58	2.09	13.2
Panel B: IPO winning information								
Winning frequency	59770	1.66	5.88	1	1	1	3	41
Winning shares (in l00 shares)	99486	7.94	7.27	5	5	5	10	25
Winning value (10 thousand RMB)	99486	1.12	1.31	0.22	0.58	0.90	1.30	4.80
Panel C: Wealth effect of IPO winning shares (at the end of the first month after winning shares)								
Profit (10 thousand RMB)	99486	0.86	1.14	-0.39	0.17	0.51	1.17	7.43
Realized Profit (10 thousand RMB)	99486	0.18	0.48	-0.02	0.00	0.00	0.11	3.03
Paper Profit (10 thousand RMB)	99486	0.66	0.93	-0.37	0.11	0.38	0.89	6.45
Profit/Portfolio Size	99486	0.17	0.48	-0.31	0.01	0.04	0.14	6.35

Table 2 Descriptive statistics of main variables in regressions

Lottery and ***MAX*** are both gambling measures of investor *i* in month *t*. Section IV.2 introduces detailed definitions of investors' gambling propensity. *Ln(InvSize)* is the natural logarithm of the portfolio value of each investor *i* at the end of month *t*. *InvTov* is the portfolio turnover of investor *i* in month *t*, which is computed as the trading value divided by the average portfolio value at the beginning and end of month *t*. All variables are winsorized at the 1% and 99% level.

Variables	**N**	**Mean**	**Sd**	**P1**	**p25**	**Median**	**p75**	**P99**
Lottery	976294	0.278	0.885	-2.201	-0.275	0.357	0.910	2.088
MAX	976294	0.137	0.897	-1.983	-0.476	0.210	0.815	1.799
ln(InvSize)	976294	2.557	1.261	0.000	1.644	2.511	3.420	5.618
InvTov	976294	0.254	0.283	0.000	0.057	0.155	0.347	1.406

Table 3 IPO lottery success and gambling behaviors: Univariate test

This table reports average gambling propensity within three months before (after) winning IPO lotteries for lottery winners ("Treated") and matched control investors ("Matched"), respectively. Gambling propensity is measured using *Lottery*. Matched control investors are constructed following the procedures described in Section V.3. The column headed "Treated–Matched" calculates the difference between lottery winners and matched control investors, and the row labeled "Post-Pre" displays changes in investors' gambling propensity after winning IPO shares. The values in bold are "difference-in-difference" estimates for the effect of IPO lottery success on subsequent investors' gambling propensity. The *t-stat* is calculated using standard errors clustered at the account level. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

	Treated	Matched	Treated–Matched	t-stat
Pre-three-month	0.252	0.250	0.002	(0.46)
Post-three-month	0.318	0.265	0.053***	(12.68)
Post-Pre	0.066***	0.015***	**0.051*****	
t-stat	(23.09)	(4.71)	**(11.79)**	

Table 4 IPO lottery success and gambling behaviors: Regression results

This table reports "difference-in-difference" estimates for the effect of IPO lottery success on investors' subsequent gambling propensity using regressions with various control variables. The dependent variable is investors' gambling propensity in month *t*, measured by *Lottery*. *Treat* is a dummy variable that equals one if an investor wins IPO shares and zero if the investor falls into matched control groups in an IPO event. *Post* is a dummy variable that equals one (zero) for months after (before) winning IPO shares. *Treat*Post* offers the "difference-in-difference" estimate. *Ln(InvSize)* is the natural logarithm of the portfolio value of each investor *i* at the end of month *t. Ln(InvTov)* is the natural logarithm of (1+*portfolio turnover*) of investor *i* in month *t. Portfolio turnover* is computed as the trading value divided by the average portfolio value at the beginning and end of month *t*. The regression results with various fixed effects are reported. The *t-statistics* calculated using standard errors clustered at the account level are reported in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)
	Dependent Variables: *Lottery*				
Treat	-0.000624				
	(-0.15)				
Post	0.0204***	0.0257***	0.00599*	-0.00859	
	(6.29)	(7.98)	(1.75)	(-1.43)	
Treat*Post	**0.0500*****	**0.0513*****	**0.0233*****	**0.0233*****	**0.0235*****
	(11.54)	**(11.95)**	**(5.31)**	**(5.31)**	**(5.35)**
Ln(InvSize)			0.0874***	0.0885***	0.0872***
			(66.83)	(66.24)	(66.23)
Ln(InvTov)			0.311***	0.335***	0.310***
			(72.53)	(72.85)	(72.17)
Account FE	No	Yes	Yes	Yes	Yes
IPO Stock FE	Yes	Yes	Yes	Yes	Yes
Calendar Month FE	No	No	No	Yes	No
Event Month FE	No	No	No	No	Yes
N	976288	976288	976288	976288	976288
R^2	0.376	0.376	0.376	0.377	0.376

Table 5 Cue salience and changes in gambling behaviors

This table explores whether the effect of IPO lottery success on investors' gambling propensity varies with cue salience. Cue salience is measured using the average winning rate of IPO lotteries (*Winning Rate*) and IPO issue-price discount (*Discount*), respectively. For each IPO stock, *Winning Rate*, the average probability of winning IPO shares, equals the number of shares issued through an online IPO lottery divided by the total number of subscriptions. *Discount* is calculated using formula

$$Discount = \frac{Close\ price - IPO\ issue\ price}{IPO\ issue\ price} \quad (6)$$

Here, *Close price* refers to the closing price of the IPO stock on the first day that is not subject to upward/downward price limits after going public, and *IPO issue price* is the issue price of IPO shares determined by underwriters. The regressions in this table are confined to the sample of lottery winners. The dependent variable is investors' gambling propensity in month *t*, measured by *Lottery*. *Post* is a dummy variable that equals one (zero) for months after (before) winning IPO shares. *Ln(InvSize)* is the natural logarithm of the portfolio value of each investor *i* at the end of month *t*. *Ln(InvTov)* is the natural logarithm of (1+*portfolio turnover*) of investor *i* in month *t*. *Portfolio turnover* is computed as the trading value divided by the average portfolio value at the beginning and end of month *t*. The *t-statistics* calculated using standard errors clustered at the account level are reported in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
	Winning Rate		Discount	
	Dependent Variables: *Lottery*			
Post	0.0135*	0.0135*	0.00318	0.00318
	(1.91)	(1.91)	(0.43)	(0.43)
Salience	0.000935*		-0.00199***	
	(1.74)		(-3.19)	
Post*Salience	**-0.00177***	**-0.00177***	**0.00389*****	**0.00389*****
	(-1.74)	**(-1.74)**	**(3.19)**	**(3.19)**
Ln(InvSize)	0.111***	0.111***	0.111***	0.111***
	(20.24)	(20.22)	(20.27)	(20.26)
Ln(InvTov)	0.232***	0.232***	0.233***	0.233***
	(33.14)	(33.12)	(33.16)	(33.14)
Account FE	Yes	Yes	Yes	Yes
IPO Stock FE	No	Yes	No	Yes
Calendar Month FE	Yes	Yes	Yes	Yes
N	526885	526885	526885	526885
R^2	0.518	0.518	0.518	0.518

Table 6 Performance changes after winning IPO shares: Univariate test

This table follows Barber and Odean (2000) to calculate changes in non-IPO portfolio performance before and after winning IPO shares for treated and matched control investors. Panel A reports the results of raw returns. We also report performance changes by calculating market-adjusted performance and characteristic-adjusted performance. We adjust raw returns using market index and corresponding Size/BM portfolio (5x5), and their results are reported in Panels B and C, respectively. Detailed definitions of performance measures are introduced in Section IV.4. The column headed "Treated–Matched" calculates the difference between lottery winners and matched control investors, and the row labeled "Post-Pre" displays changes in investor performance after winning IPO shares. The values in bold are "difference-in-difference" estimates for the effect of IPO lottery success on subsequent investment performance. The *t-stat* is calculated using standard errors clustered at the account level. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

	Treated	Matched	Treated–Matched	t-stat
Panel A Raw return				
Pre-three-month	5.62%	5.40%	0.22%	(3.10)
Post -three-month	-2.67%	-2.50%	-0.17%	(-2.28)
Post-Pre	-8.29%	-7.90%	**-0.38%**	
t-stat	(-99.67)	(-95.06)	**(-3.26)**	
Panel B Market-adjusted return				
Pre-three-month	0.52%	0.30%	0.22%	(5.22)
Post-three-month	-0.61%	-0.51%	-0.10%	(-2.26)
Post-Pre	-1.13%	-0.82%	**-0.31%**	
t-stat	(-26.95)	(-19.25)	**(-5.21)**	
Panel C Size/BM-adjusted return				
Pre-three-month	-0.74%	-0.94%	0.19%	(5.37)
Post-three-month	-1.11%	-1.04%	-0.07%	(-1.84)
Post-Pre	-0.37%	-0.11%	**-0.26%**	
t-stat	(-10.46)	(-2.93)	**(-5.15)**	

Table 7 Performance changes after winning IPO shares: Regression results

This table reports "difference-in-difference" estimates for the effect of IPO lottery success on investors' non-IPO performance using regressions with various control variables. The dependent variable is investor performance in month *t*, measured using raw return (RR), market-adjusted return (MAR), and size/BM-adjusted return (SBAR). Detailed definitions of performance measures are introduced in Section IV.4. All independent variables are defined similarly to those in Table 4. We include IPO stock fixed effects as well as investor and time fixed effects. The *t-statistics* calculated using standard errors clustered at the account level are reported in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
	RR	MAR	SBAR
Post	-0.00000172	0.000528	0.000445
	(-0.00)	(0.66)	(0.63)
Treat*Post	**-0.00326***	**-0.00230***	**-0.00169***
	(-6.35)	**(-4.69)**	**(-3.83)**
Ln(InvSize)	-0.00157***	-0.00176***	-0.00233***
	(-10.82)	(-12.68)	(-18.37)
Ln(InvTov)	-0.0193***	-0.0181***	-0.0163***
	(-29.81)	(-28.97)	(-28.80)
Account FE	Yes	Yes	Yes
IPO Stock FE	Yes	Yes	Yes
Calendar Month FE	Yes	Yes	Yes
N	859622	859622	859622
R^2	0.620	0.194	0.115

Table 8 Changes in gambling behaviors and performance changes

This table explores whether performance changes around the IPO lottery are attributable to changes in investors' gambling propensity. For each treated investor, DID^{VAR} is a "difference-in-difference" change of VAR relative to his/her matched control investor, which is identified by estimating the coefficient of *Treat X Post* using formula (8):

$$VAR = b_0 + b_1 Treat + b_2 Post + b_3 Treat * Post + e \quad (7)$$

VAR indicates variables exploited in the regressions, including investor-level gambling propensity (*Lottery*), investor portfolio turnover (*Ln(InvTov)*), and investment performance (raw return, market-adjusted return, and size/BM-adjusted return). *Treat* is a dummy variable that equals one (zero) for treated (control) investors. *Post* is a dummy variable that equals one (zero) for months after (before) winning IPO shares. *Avg. Ln(InvSize)* denotes the average natural logarithm of the investor portfolio market value during three months before winning IPO shares. The *t-statistics* calculated using robust standard errors are reported in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
	DID^{RR}	DID^{MAR}	DID^{SBAR}
$DID^{Lottery}$	-0.00692***	-0.00850***	-0.00549***
	(-8.16)	(-8.04)	(-5.50)
$DID^{\ln(InvTov)}$	0.0327***	0.0321***	0.0256***
	(4.56)	(4.29)	(8.81)
Avg. Ln(*InvSize*)	-0.00113	-0.00223	0.000561
	(-1.01)	(-1.44)	(0.55)
Constant	-0.000379	0.00306	-0.00408*
	(-0.14)	(0.80)	(-1.71)
N	62737	62737	62737
R^2	0.008	0.010	0.006

Table 9 House money effect

This table compares the effect of gains from IPO lotteries on investors' subsequent gambling propensity with that of prior performance of non-IPO stocks by estimating the following regression equation:

$$Gambling_{i,t} = b_0 + b_1 IPO\ \ Profit_{i,[t-3,t-1]} + b_2 Performance_{i,[t-3,t-1]} + Controls + e_{i,t} \quad (8)$$

Here, *i* denotes investor and *t* denotes calendar month. We measure investors' gambling propensity using *Lottery*. *IPO Profit* is gains from winning IPO shares within the past three months divided by one's portfolio value. We follow Barber and Odean (2000) to calculate trading performance among non-IPO stocks of investor *i* within the past three months (*Performance*). In Panel A, we run regressions only among the sample of treated investors. In Panel B, we include both treated investors and matched control investors in the regressions. The *t-statistics* calculated using standard errors clustered at the account level are reported in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

Panel A Treated Investors

	(1)	(2)	(3)
	Dependent Variables: *Lottery*		
IPO Profit	0.426***	1.535***	1.281***
	(5.06)	(21.68)	(17.43)
Performance	0.145***	0.192***	0.372***
	(33.85)	(50.93)	(58.96)
Account FE	No	Yes	Yes
Calendar Month FE	No	No	Yes
N	2433644	2433644	2433644
R^2	0.001	0.300	0.303

Panel B All Investors

	(1)	(2)	(3)
	Dependent Variables: *Lottery*		
IPO Profit	0.645***	1.497***	1.213***
	(7.13)	(21.67)	(17.21)
Performance	0.149***	0.196***	0.373***
	(33.45)	(50.56)	(57.51)
Account FE	No	Yes	Yes
Calendar Month FE	No	No	Yes
N	4881007	4881007	4881007
R^2	0.001	0.296	0.299

Table 10 Wealth effect

We first classify investors into the "Large" ("Small & Medium") group when their average portfolio value during the three months before event month market is larger (smaller) than 1 million RMB. We then rerun baseline regressions in each group. We control for dynamic investor characteristics, IPO stock fixed effects, account fixed effects, and calendar month fixed effects in all regressions. The *t-statistics* calculated using standard errors clustered at the account level are reported in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

	(1)	(2)
	Small & Median	Large
	Dependent Variables: *Lottery*	
Post	-0.00579	-0.0543***
	(-1.06)	(-3.05)
Treat*Post	**0.0205*** **	**0.0528*** **
	(6.47)	**(5.37)**
Ln(InvSize)	0.0929***	0.00702
	(77.96)	(0.41)
Ln(InvTov)	0.339***	0.254***
	(91.53)	(9.38)
Account FE	Yes	Yes
IPO Stock FE	Yes	Yes
Calendar Month FE	Yes	Yes
N	895961	64043
R^2	0.379	0.589

Table 11 IPO Lottery Success and Overall Investment

This table explores the effect of IPO lottery success on overall investment in stock markets using the "difference-in-difference" approach similar to our baseline regressions. The dependent variable is an investor's net buy (i.e., dollar purchase minus dollar sale) in month t divided by total trading volume in this month (or portfolio value at the end of month t-1). All independent variables are defined similarly to those in Table 4. We include IPO stock fixed effects as well as investor and time fixed effects. The t-statistics calculated using standard errors clustered at the account level are reported in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
	Net Buy / Trading Volume		Net Buy / Portfolio Value	
Post	0.0487^{***}	-0.00478^{*}	0.0429^{***}	-0.00446^{**}
	(30.24)	(-1.72)	(29.13)	(-2.00)
Treat*Post	$\mathbf{-0.0328^{***}}$	$\mathbf{-0.0301^{***}}$	$\mathbf{-0.00502^{***}}$	**-0.000968**
	(-18.10)	**(-16.55)**	**(-3.01)**	**(-0.58)**
Ln(InvSize)	-0.111^{***}	-0.139^{***}	-0.112^{***}	-0.149^{***}
	(-72.60)	(-73.93)	(-46.62)	(-48.95)
Ln(InvTov)	-0.0397^{***}	-0.0417^{***}	0.0278^{***}	0.0303^{***}
	(-17.09)	(-16.30)	(7.29)	(6.20)
IPO FE	Yes	Yes	Yes	Yes
Account FE	Yes	Yes	Yes	Yes
Calendar Month FE	No	Yes	No	Yes
N	972902	972902	972902	972902
R^2	0.281	0.286	0.268	0.272

Table 12 Trading experiences and investors' responses to lottery cues

This table examines whether trading experiences attenuate the magnitude of investors' responses to lottery cues. We measure trading experiences with the length of time investors that spend in stock markets. Specifically, *Account Age* is the cumulative number of months from one's first trading month in our sample to the month winning IPO shares. *Experienced* is a dummy variable, which equals one if the account has over two years' trading records upon winning IPO shares and zero otherwise. We estimate the equation (9) and equation (10), respectively, among lottery winners. IPO event fixed effects, account fixed effects, and calendar month fixed effects are all included.

$$Gambling_{ijt} = a_0 + a_1 Post_{jt} + a_2 Post_{jt} * Account\ \ Age_i + Controls + e_{ijt} \quad (9)$$

$$Gambling_{ijt} = b_0 + b_1 Post_{jt} + b_2 Post_{it} * Experienced_i + Controls + e_{ijt} \quad (10)$$

Here i, j, and t indicates investor, IPO event, and calendar month, respectively. The *t-statistics* calculated using standard errors clustered at the account level are reported in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
	Dependent Variables: *Lottery*			
Post	0.0252***	0.0287***	0.0189***	0.0198***
	(4.38)	(3.41)	(4.06)	(2.60)
Post*Account Age	**-0.00485******	**-0.00674******		
	(-3.27)	**(-3.64)**		
Post*Experienced			**-0.0152******	**-0.0193******
			(-2.70)	**(-2.67)**
Ln(InvSize)	0.107***	0.103***	0.108***	0.106***
	(23.38)	(17.32)	(23.84)	(18.25)
Ln(InvTov)	0.216***	0.237***	0.214***	0.235***
	(32.59)	(33.27)	(32.72)	(33.18)
Account FE	Yes	Yes	Yes	Yes
IPO Stock FE	Yes	Yes	Yes	Yes
Calendar Month FE	No	Yes	No	Yes
N	526037	526037	526037	526037
R^2	0.517	0.519	0.517	0.519

Table 13 Prior performances and investors' responses to lottery cues

In this table, we divide treated investors into subgroups by their portfolio performance over three months before winning an IPO lottery. Investors with losses (gains) are equally divided into two subgroups and labeled "Large loss" ("Large Gain") and "Small Loss" (Small Gain), respectively. In each subgroup, we then estimate the following regression:

$$Gambling_{ijt} = a_0 + a_1 Post_{jt} + Controls + e_{ijt} \tag{11}$$

All variables are defined similarly to those in Table 4. In Panel A (B), we measure investors' performance using raw returns (size/BM-adjusted returns). We include investor fixed effects in all regressions. The *t-statistics* calculated using standard errors clustered at the account level are reported in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

Panel A Measuring investors' performance using raw returns

	(1)	(2)	(3)	(4)
	Dependent Variables: *Lottery*			
	Large Loss	Small Loss	Small Gain	Large Gain
Post	-0.0431***	0.00204	-0.00809	0.0367***
	(-4.85)	(0.20)	(-1.15)	(5.14)
Ln(InvSize)	0.0926***	0.0896***	0.113***	0.110***
	(6.38)	(5.68)	(13.57)	(12.41)
Ln(InvTov)	0.184***	0.183***	0.210***	0.251***
	(10.60)	(9.71)	(16.01)	(18.94)
Account FE	Yes	Yes	Yes	Yes
N	68600	69436	143168	148404
R^2	0.514	0.530	0.506	0.530

Panel B Measuring investors' performance using size/BM adjusted returns

	(1)	(2)	(3)	(4)
	Dependent Variables: *Lottery*			
	Large Loss	Small Loss	Small Gain	Large Gain
Post	-0.0374***	-0.000258	0.0170*	0.0473***
	(-5.16)	(-0.04)	(1.95)	(5.07)
Ln(InvSize)	0.108***	0.123***	0.119***	0.0948***
	(11.55)	(12.33)	(10.35)	(8.29)
Ln(InvTov)	0.212***	0.227***	0.215***	0.220***
	(16.08)	(15.53)	(12.56)	(13.85)
Account FE	Yes	Yes	Yes	Yes
N	126379	126961	88205	88063
R^2	0.500	0.530	0.533	0.517

Table A1 Baseline Regression Results Using Alternative Gambling Measures

This table reports "difference-in-difference" estimates for the effect of IPO lottery success on investors' subsequent gambling propensity using regressions with various control variables. The dependent variable is investors' gambling propensity in month *t*, measured by *MAX*. *Treat* is a dummy variable that equals one if an investor wins IPO shares and zero if the investor falls into matched control groups in an IPO event. *Post* is a dummy variable that equals one (zero) for months after (before) winning IPO shares. *Treat X Post* offers the "difference-in-difference" estimate. *Ln(InvSize)* is the natural logarithm of the portfolio value of each investor *i* at the end of month *t*. *Ln(InvTov)* is the natural logarithm of (1+*portfolio turnover*) of investor *i* in month *t*. *Portfolio turnover* is computed as the trading value divided by the average portfolio value at the beginning and end of month *t*. The regression results with various fixed effects are reported. The *t-statistics* calculated using standard errors clustered at the account level are reported in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)
	Dependent Variables: *MAX*				
Treat	-0.00567				
	(-1.40)				
Post	-0.00001	0.000263	-0.00688*	-0.0243***	
	(-0.02)	(0.08)	(-1.89)	(-3.75)	
Treat*Post	**0.0497*****	**0.0498*****	**0.0328*****	**0.0276*****	**0.0328*****
	(10.76)	**(10.77)**	**(6.96)**	**(5.88)**	**(6.95)**
Ln(InvSize)			0.0382***	0.0434***	0.0385***
			(25.94)	(28.83)	(25.97)
Ln(InvTov)			0.238***	0.282***	0.237***
			(50.81)	(56.18)	(50.49)
Account FE	No	Yes	Yes	Yes	Yes
IPO Stock FE	Yes	Yes	Yes	Yes	Yes
Calendar Month FE	No	No	No	Yes	No
Event Month FE	No	No	No	No	Yes
N	976288	976288	976288	976288	976288
R^2	0.277	0.277	0.277	0.281	0.277

Table A2 Robustness check: standard errors clustered by both account and calendar month

This table reports the results of main baseline regressions in Table 4 when calculating *t*-statistics using standard errors clustered by account and calendar month.

	(1)	(2)	(3)
	Dependent Variables: *Lottery*		
Post	0.00599**	-0.00859	
	(2.06)	(-1.41)	
Treat*Post	**0.0233*****	**0.0233*****	**0.0235*****
	(6.26)	**(6.26)**	**(6.31)**
Ln(InvSize)	0.0874***	0.0885***	0.0872***
	(68.67)	(68.00)	(68.05)
Ln(InvTov)	0.311***	0.335***	0.310***
	(76.52)	(76.81)	(76.17)
Account FE	Yes	Yes	Yes
IPO Stock FE	Yes	Yes	Yes
Calendar Month FE	No	Yes	No
Event Month FE	No	No	Yes
N	976288	976288	976288
R^2	0.376	0.377	0.376

Table A3 Robustness checks: alternative ways to construct the control sample

This table reports the results of baseline regressions when constructing the control sample in alternative ways. In Column (1) and (2), we only require that investors in the "filtered control group" *do not* have successful IPO lottery experiences within three months before and after the event month. We then add more restrictions to the control sample. In Column (3) and (4), we require that investors in the "filtered control group" should have at least one successful IPO lottery experience three months before or after the event month. In Column (5) and (6), we require that investors in the "filtered control group" should have at least one successful IPO allotment three months before the event month. Variable definitions and model specifications are similar to those in Table 4. The *t-statistics* calculated using standard errors clustered at the account level are reported in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variables: *Lottery*					
Post	-0.0171**		-0.0222***		-0.0185***	
	(-2.57)		(-3.33)		(-2.69)	
Treat*Post	**0.0425*****	**0.0428*****	**0.0447*****	**0.0451*****	**0.0324*****	**0.0326*****
	(8.68)	**(8.73)**	**(9.11)**	**(9.18)**	**(7.69)**	**(7.73)**
Ln(InvSize)	0.0956***	0.0940***	0.102***	0.100***	0.100***	0.0981***
	(59.21)	(59.45)	(63.59)	(63.59)	(65.04)	(64.92)
Ln(InvTov)	0.387***	0.358***	0.405***	0.372***	0.415***	0.378***
	(68.12)	(67.90)	(70.09)	(69.54)	(74.57)	(73.22)
Account FE	Yes	Yes	Yes	Yes	Yes	Yes
IPO Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Month FE	Yes	No	Yes	No	Yes	No
Event Month FE	No	Yes	No	Yes	No	Yes
N	783554	783554	783774	783774	786819	786819
R^2	0.373	0.371	0.368	0.366	0.366	0.364