Does Good Luck Make People Overconfident? Evidence from a Natural Experiment in China*

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Abstract

This paper examines the changes in trading behavior for retail investors who win an allotment for the IPO subscription. We find that retail investors who win such an allotment subsequently become more overconfident relative to retail investors who do not: the former group trade more frequently and lose more money. This effect is not explained by the wealth effect or house money effect. Overall, our evidence indicates that the experience of good luck makes people more overconfident about their prospect.

Keywords: Good Luck; Turnover rate; Trading; Overconfidence; IPO Subscription

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1. Introduction

Overconfidence is a widely documented cognitive bias that significantly influence individual's decision making (see, for example, Thaler and Johnson, 1990). While most of these studies focus on the influence of overconfidence, little is known on what makes people overconfident in the first place. In this paper, our research question is: does the experience of good luck make people overconfident about their prospect in the future? We measure "good luck" by exploiting a natural experiment: households who win the allotment in IPO subscription. We use retail investors' stock trading behavior to infer their "overconfidence", following Barber and Odean (2001).

Borrowing the theoretical framework of Gervais and Odean (2001) on learning to be overconfident[1], we hypothesize that the trader believes in luck and can learn whether he is in a lucky stage at a given period may depend on their recent experience of "lucky events." People who recently experience "good luck" may revise up their subjective probability of being lucky too much and thus become overconfident about their prospect.

The unique feature of winning the lot in IPO subscription allows us to estimate its effects in a difference-in-differences framework. Ideally, to study an experiment's effect, one would like to have an exogenous experiment in which individuals were randomly assigned to be affected by the experiment, which would allow us to compare treated and non-treated individuals' outcomes and to attribute any differences to the experiment. In China, winning the allotment in IPO subscription could be something very close to such an experiment. Individual investors who applied for IPO

[1] In their model, a trader learns his ability by his past success or failure. When a trader is successful, he attributes too much of his success to his own ability and revise up his belief about his ability too much, which leads to overconfidence about this ability. This their model, traders learn their ability from the past experience and the bias (such as self-serving attribution bias) in the learning process leads to overconfidence about their true ability. The more overconfident an investor, the more he trades and the lower his expected profits from trading.

allotment will be assigned an IPO application number for each 1,000 share[2] they are applying for firms to be listed on Shanghai Stock Exchange. This IPO application number is randomly assigned by China Securities Depository and Clearing Corporation (CSDC) and cannot be changed. The winning allotment numbers are drawn randomly from the pool with the entire process being taped and audited. Moreover, China's IPO is greatly underpriced and households could make some considerable amount of money if they luckily win the allotment. Thus, winning IPO allotment is a good setting to measure how "being lucky" influences people's subsequent behavior.

We empirically test the effect of winning IPO allocation on retail investors' stock trading behavior using a panel of over eight million person-period observations of Chinese individual investors during 2014–2016 and a difference-in-differences approach. We find that winning IPO allocation (a proxy of good luck) leads to a more frequent but less profitable trading (a reflection of overconfidence). On average, individuals who win the IPO allocation experience an increase in turnover rate by 14 percentage points and a decrease in their portfolio return by 1 percentage point, relative to individuals who fail to win the IPO allocation.

It is worth noting that our results are unlikely driven by the house money effect, which generally refers to the pattern that people tend to take on increased risk subsequent to a successful investment experience because they do not fully integrate the new money as their own but regard the new money as the house's money (Thaler and Johnson, 1990). We focus on the individual's overall portfolio trading, rather than the trading of new IPO shares. In other words, we focus on how individuals trade their pre-existing money after winning the IPO allocation. In contrast, the house money effect should predict that individuals take more risk with the new money they earn

[2] Investors with average stock portfolio worth at least 10,000 RMB in day t-20 to day t-2 relative to IPO offer day can apply for IPO allotment. Each 5,000 is qualified for one allotment ticket which corresponds to 1,000 IPO shares. The allotment application must be less than 0.1% of total IPO shares. Investors will learn their application results on day t+2.

from the IPO shares, but provide no prediction on how individuals deal with their pre-existing money. Second, given that high risk is usually associated with high return (at least for raw return), the house money effect would predict that individuals could have higher raw return subsequently. However, this is opposite to our findings.

It is also worth noting that our results are unlikely driven by wealth effect (i.e., the effect of winning IPO allocation on trading is because the individuals become rich). First, depending on the assumption of standard utility function, wealth could be positively or negatively correlated with risk preference. Thus, from an ex-ante perspective, it is unclear how the wealth gain from winning the IPO allocation would influence individuals' subsequent trading behavior. Second, we later re-estimate our results based on a subsample of rich individuals (for example, the ones with total portfolio value greater than 5 million RMB). Given that the average dollar gain of winning IPO allocation is around 30 thousand RMB, it should have no meaningful "wealth effect" on rich individuals. However, our results are largely the same when focusing on the subsample of extremely rich individuals.

This paper provides at least two major contributions to the existing literature. First, our study is related to the literature on reinforcement learning, which posits that people' choice of actions depends on the payoffs they obtained from the same actions in the past (Erev and Roth 1998; Camerer and Ho 1999). Kaustia and Knupfer (2008) show that individuals' experience of high IPO return lead to more IPO subscription in the future. Choi et al. (2009) report that high personally experienced returns in 401(k) accounts induce higher 401(k) savings rates. Greenwood and Nagel (2009) find that young mutual fund managers chose higher exposure to technology stocks in the late 1990s than older managers. Similarly, Vissing-Jorgensen (2003) shows that young retail investors with little investment experience had the highest stock return expectations

during the stock-market boom in the late 1990s. Malmendier and Nagel (2011) show that individuals who have experienced low stock-market returns (the Great Depression period) are less willing to participate in the stock market. Malmendier and Nagel (2016) show that difference in life expectation strongly predict differences in subjective inflation expectations. Complementing to this literature, our study suggests that past experience of "good luck" in the stock market makes people overconfident about their prospect in the future.

Second, there is a large literature focusing on how overconfidence influences people's decision making. Taking individual investors for example, overconfidence makes these investors trade more and lose more money (Barber and Odean, 2001). Taking corporate executives for examples, overconfident CEOs usually invest more, make more acquisitions (Malmendier and Tate 2005, 2008). Complementing this strand of literature, which usually take overconfidence as given, we investigate why individuals become overconfident in the first place? Does certain past experience increase the level of overconfidence in the future? We provide evidence that past experience of good luck is an important factor leading people overconfident about their prospect in the future.

The remainder of the paper is organized as follows: Section 2 reviews the background of China's IPO allotment; Section 3 develops our hypothesis; Section 4 describes our sample and key variable construction; Section 5 presents the empirical results; and Section 6 concludes.

2. Background on China's allocation of IPO Shares

IPO market is a hot investment topic on China A-share market. IPO process has gone through several stages. Prior to 2001, in order to protect investors when the market and investors are relatively immature and market mechanism is relatively incomplete, China Securities and

Regulation Committee (CSRC) adopted an approval method to control total IPO volume, with regulated IPO pricing method. IPO were priced at fixed price before 1993, companies do not have rights to determine issue price. During 1994-1998, IPO prices were fixed between 13-16 times PE ratio. From the end of 1998, IPO pricing started to be determined by the market. However, due to the increasing IPO price and PE ratio, many newly listed firms' prices drop after they went public, there were resentment towards high IPO price. PE multiple fixed pricing became the IPO pricing method since November 2001.

The new securities law in 2004 canceled the requirement that IPO price must be approved by the regulator. IPO price were determined by the market since 2005. IPO market shows high price and significant first day price drop.

CSRC started stricter "window guidance" for IPO after 2014, and put on strict restriction on PE ratio, forced PE ratio to be below 23 times. However, since 23 times PE ratio is significantly below the market expected price, IPO stocks will normally increase 44% on the first day[3], and reach price limit of 10% for several trading days afterwards.

All investors with qualified holdings can apply for IPO allotment. Investors needs to have 10,000 RMB worth of stocks on average during day t-20 to t-2 period relative to IPO day. For each 5,000 RMB worth of stock, investor can apply for one allotment ticket on day t. One allotment ticket corresponds to 1,000 IPO shares. No investor can apply for more than 0.1% of total IPO volume for a single firm. The tickets will be drawn randomly under audit on day t+1, and investors will learn their application results on day t+2. On average, there are 11 days between IPO allotment application day and IPO public trading day.

[3] It is regulated that first day return cannot exceed 44%. As a result, all stocks price increase by 44% on the first day.

The average winning probability for IPO allotment application is 0.48% in our sample period from June 30, 2014 to September 1, 2016. The winning probability is substantially low. However, once win the allotment application, investor can get at least 44% first day return. On average, investors will reap around 30,000 RMB (around 4,600 USD) profit by winning one IPO allotment application.

3. Hypothesis Development

Our theoretical framework follows the model developed by Gervais and Odean (2001), who show that overconfidence is determined endogenously and changes dynamically based on a trader's past success or failure. When a trader is successful, he attributes too much of his success to his own ability and revise up his belief about his ability too much, which leads to overconfidence about this ability. This their model, traders learn their ability from the past experience and the bias (such as self-serving attribution bias) in the learning process leads to overconfidence about their true ability. The more overconfident an investor, the more he trades and the lower his expected profits from trading.

Although traders donot learn "luck" in their model, one can easily extend their idea from "learning ability" to "learning luck." The outcomes of many risky decisions depend on both ability and luck. In general, economic theories assume that luck is a random, uncontrollable factor which should have little effect on future expectations. Although this is certainly correct scientifically, many people seem to think of luck in a manner that is discrepant with this view. In reality, it is common to see that some people "believe in luck," meaning that they think good luck consistently produces success in their daily lives. People sometimes say they have lucky days or that they think of themselves as lucky people in general. For example, Michael Jordan (a professional basketball player for the Chicago Bulls) changed the number on his uniform to

"change his luck," following a series of disappointing performance.[4] These kinds of statements imply that luck is viewed as a personal quality that is at least somewhat stable at least over a short period of time.

Extending Gervais and Odean's (2001) framework of learning ability, the trader can learn whether he is in a lucky stage at a given period may depend on their recent experience of "lucky events." People who recently experience "good luck" may revise up their subjective probability of being lucky too much and thus become overconfident about their prospect. Supporting this conjecture, Darker and Freeman (1997) provide evidence that people react to lucky events by becoming more positive about the likelihood of future success, and such irrational beliefs about luck can serve as a source of positive expectations for the outcome of future events. This will lead to excessive (and inefficient) trading, similar in spirit to overconfidence about ability.

In summary, considering that we use event of winning IPO allotment as a measure of good luck and turnover rate as a proxy for traders' overconfidence, we predict that traders increases their trading following the winning of IPO allotment.

4. Sample Formation and Variable Construction

All our data is obtained from Shanghai Stock Exchange, which record all individuals' trading activities on the stock exchange. Our data set covers three main files: trading, holding, and account type. In the trading file, we have account-trade level data that cover the common trade variables, with security code, encrypted account identifier, trade price, trade volume, trade direction, and the date and time of the trade. The holdings file is recorded daily to reflect each account's end-of-day holdings. The holdings variables include encrypted account identifier, date,

[4] Jordan goes back to No. 23 (1995, May 11). *USA Today*, p.8C.

security code, holding balance, and effective date. The account type file classifies each account under a specific type, including retail, mutual fund, qualified foreign institutional investor, social security fund, insurance firm, brokerage asset management, broker self- account, hedge fund, and other institutions. In our study, we look at all individual investor accounts.

We look at the IPO event from June 30, 2014 to September 1, 2016. Hence our sample is from the February 2014 to December 2016. We first identify the individuals who win the IPO allocation (the treated group). We can track the stock trading behavior over three months prior to the IPO and three months after the IPO with the most recent one month data omitted. For each three-month period, we calculate their turnover rate and performance of trading. As we explained in Section 2, the likelihood of winning the IPO allotment may be positively associated with investor's wealth. Thus, for each treated household, we match him to a control household who did not win the IPO allotment but has the closest portfolio value in the three-month period prior to the IPO subscription. Considering the trading of new IPO shares may bias our results and we are interested in investors' trading behavior in their existing portfolio, we remove the trading of the new IPO stock for both treated and control group. Finally, we have 4,142,912 person-period for the treated group and 4,142,912 person-period for the control group.

Following Barber and Odean (2001), our first measure of turnover is the average of buy volume and sell volume divided by the average portfolio size. As an alternative measure, we also measure turnover rate by taking the minimum of buy and sell volume divided by the average portfolio size.

To gauge the effect of overconfident trading on return performance, we calculate an "own-benchmark" abnormal return for individual investors following Barber and Odean (2001). The benchmark is the three month return of the beginning of period portfolio (month t-4 for pre-event,

and month t+1 for post-event) held by individual *i*, denoted R_i^b, which represents the return that the individual would have earned by holding its beginning of period portfolio for the three month. In gross own-benchmark abnormal return is the real return for each investor over the three month period minus the benchmark return.

To remove those inactive account, we dropped accounts with zero trading in that year. We also require investors to have average portfolio size to be more than 10,000 RMB in month t-4 to month t-1 prior to IPO date, this criterion will also remove those accounts that only participate on the IPO market only.

Table 1 provides summary statistics. On average, households in our sample hold a stock portfolio value of 0.4 million RMB, and have a turnover rate of around 400% of their entire portfolio. Their raw portfolio return is 11.1% and own-benchmark abnormal return is 7%.

5. Empirical Results

5.1 Univariate Tests

We examine the before-after effect of the change in trading behavior for the treatment group compared to the before-after effect in the control group. Table 2 reports the univariate test. For each household, we compute the change in the turnover rate as:

$$\Delta Turnover\ rate = Turnover\ after\ the\ IPO\ allotment - Turnover\ before\ the\ IPO\ allotment.$$

The average $\Delta Turnover1$ is 33% for the treated group, and 19% for the control group. This indicates that the average investors in the treated group increase their turnover rate by 33 percentage points on average around the IPO allotment, while the average investors in the control group only increase their turnover rate by 19 percentage points. Such a difference is significant at the 1% level. Our inference is largely the same when using *Turnover2*.

In terms of portfolio return, the average $\Delta Raw\ return$ is -20% for the treated group, and -19% for the control group. This indicates that the average investors in the treated group experience a decrease in their portfolio return by 20 percentage points around the IPO allotment, while the average investors in the control group experience a decrease in their portfolio return by 19 percentage points. Such a difference is significant at the 1% level. The average $\Delta Abnormal\ return$ is -14.7% for the treated group and -13.8% for the control group, indicating that the average investors in the treated (control) group experience a decrease in their portfolio abnormal return by 14.7 (13.8) percentage points around the IPO allotment. Such a difference is also significant at the 1% level.

It is worth noting that there is a significant change in turnover rate and portfolio return even for the control group. This is not surprising because our IPO sample largely overlap the 2015–16 Chinese stock market turbulence.[5]

Overall, the univariate test shows that treated group trade more and lose more money for their portfolio after winning the IPO allotment, compared to the control group. This result indicates that the experience of winning IPO allotment makes people become more overconfident subsequently.

5.2 Turnover rate

[5] The Chinese stock market turbulence began with the popping of the stock market bubble on 12 June 2015 and ended in early February 2016.A third of the value of A-shares on the Shanghai Stock Exchange was lost within one month of the event. Major aftershocks occurred around 27 July and 24 August's "Black Monday". By 8–9 July 2015, the Shanghai stock market had fallen 30 percent over three weeks as 1,400 companies, or more than half listed, filed for a trading halt in an attempt to prevent further losses. Values of Chinese stock markets continued to drop despite efforts by the government to reduce the fall. After three stable weeks the Shanghai index fell again on 24 August by 8.48 percent, marking the largest fall since 2007. By the end of December 2015 China's stock market had recovered from the shocks and had outperformed S&P for 2015, though still well below the 12 June highs. By the end of 2015 the Shanghai Composite Index was up 12.6 percent. In January 2016 the Chinese stock market experienced a steep sell-off and trading was halted on 4 and 7 January 2016 after the market fell 7%, the latter within 30 minutes of open. The market meltdown set off a global rout in early 2016. After this last turbulence, the Shanghai Composite Index has been stable around 3,000 points, 50% more than before the bubble popped.

We implement a standard difference-in-differences test through the following regression:

$$Turnover = \alpha + \beta_1 Treat \times Post + \beta_2 Treat + \beta_3 Post + \beta_4 Ln\,(Portfolio\ Wealth) + \beta_5 Market\ performance + \varepsilon. \quad (1)$$

The dependent variable is the turnover rate of an individual's portfolio. The indicator variable *Treat* takes the value of one for the treated group, and zero for the control group. The indicator variable *Post* takes the value of one for the three-month period after winning the IPO allotment, and zero for the three-month period prior to winning the IPO allotment. We control for the portfolio wealth (measured at the beginning of each three-month period) and the return of the stock market index. Given that our treatment is defined at the person level, we cluster standard errors by person.

The coefficient of interest in this model is the $\beta_1$coefficient, which captures the turnover differences in treated group before and after the event as opposed to similar before-after differences in control groups.

It is helpful to consider an example. Suppose we want to estimate the effect of winning an IPO allotment on a person's trading behavior. We can subtract the turnover rate before the event from the turnover rate after the event for persons that win the IPO allotment. However, economy-wide shocks may occur at the same time and affect people's trading behavior. To difference away such factors, we calculate the same difference in turnover rate for persons who donot win the IPO allotment. Finally, we calculate the difference between these two differences, which represents the incremental effect of winning an IPO allotment on the treated group compared to the control group.

Table 3 presents the regression results. The coefficient estimates on *Treat*×*Post* are positive and statistically significant in all columns. The dependent variable in column (1) is the turnover rate, calculated as min(buy, sell)/average portfolio value. We include *Treat*×*Post, Treat,*

Post in the regression. We find that the coefficient on *Treat*×*Post* is positive and significant at the 1% level, suggesting that people trade more after they win the IPO allotment. We additionally control for Ln (Wealth) and the return of the stock market index in column (2), and the coefficient on *Treat*×*Post* is 0.14 and significant at the 1% level. The economic magnitude is sizable: turnover rate increase by 14 percentage points after winning the IPO allotment, relative to the sample median turnover rate of 176 percentage points (i.e., an increase of approximately 8%).

In columns (3) and (4), we use half buy turnover+half sell turnover as an alternative way to compute turnover rate, and we continue to find that investors tend to trade more after winning an IPO allotment. Taking column (4) for example, the coefficient on *Treat*×*Post* is a significant 0.099, indicating that turnover rate increases by approximately 10 percentage points (or 5%) following the winning of the IPO allotment, relative to the sample median of 213 percentage points.

With regards to control variables, we find that people with a large portfolio value tend to trade less and people tend to trade more when the stock market is booming. These results are broadly consistent with prior literature (e.g., Barber and Odean, 2001).

Taken together, these results indicate that people tend to trade more after they win the IPO allotment.

5.3 Portfolio Return

In this section, we examine the return of individuals. Examining the return could further help to distinguish whether increased turnover rate is due to increased overconfidence or due to some rational response made by the individuals. The changes in the trading behavior reflects any kind of rational response made by the individuals, it should predict that the stock performance of these individuals should not become worse. One example of such rational response could be: winning the IPO allotment could affect a person's risk preference and make him more risk-seeking.

Thus, high turnover rate could simply reflect a change in risk-taking preference. However, this type of explanation could predict higher raw return in the post-event period considering that high risk is positively associated with high raw return. In contrast, our overconfidence implies that investors mistakenly over-estimate her prospect in the stock market, and thus predict that these trading could be associated with lower return.

We re-estimate Equation (1) by using the person's portfolio return as the dependent variable. In columns (1) and (2) of Table 4, we use the raw return as the dependent variable. The coefficient on *Treat*×*Post* is significantly negative in both columns. Taking column (2) for example, the coefficient on *Treat*×*Post* is -0.009 and is significant at the 1% level. This result indicates that individuals in the treated group experience a decrease in raw return by 0.9 percentage points over the three-month period following the winning of the IPO allotment.

In columns (3) and (4), our dependent variable is the own-benchmark abnormal return, which represents the return that the household would have earned if it had merely held its beginning-of-period portfolio for the entire period. Taking column (4) for example, the coefficient on *Treat*×*Post* is -0.01 and is significant at the 1% level. This result indicates that households in the treated group experience a decrease their own-benchmark abnormal return by one percentage point over the three-month period following the winning of the IPO allotment.

Overall, Table 4 shows that, after winning the IPO allotment, households earn significantly lower return compared to the households in the control group. This result is also consistent with the view that higher turnover rate after the IPO allotment reflect overconfidence rather than any rational response made by the household.

5.4 Wealth Effect?

Could our results be explained by wealth effect? That is, households in the treatment group trade more because they become richer after winning the IPO allotment. This explanation is unlikely to hold for the following reasons. First, from an ex ante perspective, it is unclear how whether wealthy people trade more or less. Depending on the assumption of people's utility function, people's risk preference may increase or decrease with their wealth level. Assuming that trading activities is positively correlated with stronger risk-seeking preference, household may trade more or less after becoming wealthy. Second, even if we assume that households become more risk-tolerant after becoming richer and thus trade more, this explanation is inconsistent with our results that the portfolio return of these households become worse as high risk should be correlated with high return. Third, to provide a formal test to examine the wealth effect, we re-estimate our main results by focusing on the subsample of wealthy individuals. As we explained in Section 2, the average RMB-gain of winning the IPO allotment is around 30,000 RMB. If the household is very wealthy in the first place, then the wealth effect of winning the IPO allotment is trivial.

In Table 5 Panel A, we focus on the group of households whose portfolio wealth is in the top 10% of all households in our sample, and re-estimate their changes in turnover rate and portfolio return. The regression specification in columns (1) and (2) of Table 5 is the same as that in columns (2) and (4) of Table 3. The coefficients on the *Treat*×*Post* indicator are still significantly positive and the economic magnitude is even larger than that in the baseline regression. Taking column (1) for example, the coefficient on *Treat*×*Post* is 0.147 and significant at the 1% level, indicating that turnover rate increases by approximately 15 percentage points after winning the IPO allotment. Considering that winning the IPO allotment increases turnover rate by 14 percentage points (see

column (2) of Table 3), our results are slightly stronger for the group of highly wealthy of households, which suggests that wealth effect is unlikely to explain our findings.

In columns (3) and (4) of Table 5 Panel A, we examine the raw return and own-benchmark abnormal return of the household's portfolio. The regression specification is same as that in column (2) and column (4) of Table 4. We continue to find that households experience a significant drop in their portfolio return after winning the IPO allotment. The coefficients on the *Treat*×*Post* indicator are -0.016 and -0.014, respectively, and both of them are significant at the 1% level. For the group of highly wealthy household (for whom the wealth effect of winning IPO allotment is trivial), the raw return and own-benchmark abnormal return decrease by 1.6 and 1.4 percentage points, respectively. Such effects are even larger than the ones reported in our full sample (see column (2) and (4) of Table 4).

In Table 5 Panel B, we re-estimate Panel A by focusing on the group of households whose portfolio wealth is at least 5 million RMB. Such a restriction greatly reduces our sample to less than 80,000 person-period observations, because only very a small number of households are such wealthy. We continue to find that our results are almost the unchanged (or even stronger) for such group of highly wealthy people. Taking column (1) for example, the turnover rate increases by 20 percentage points following the winning of the IPO allotment (even the wealth gain relatively trivial).

Overall, these results indicate that our findings are unlikely to be explained by the wealth effect.

5.5 Fixed Effect Regression

The data from Shanghai Stock Exchange do not provide much demographic information, such as gender, age, education, profession, and so on. Given that our tests are in the difference-in-

differences setting and examines the change in trading activities for treated households over six months around winning the IPO allotment as compared to the change for matched households in the control group, this demographic information is largely time-invariant and should not affect our results. Nonetheless, we additionally control for person fixed effect in the regression to control for all these time-invariant factor. The results are reported in Table 6. After controlling for person fixed effect, the variable *Treat* is omitted because it is absorbed by the fixed effect. The significance and magnitude of *Treat*×*Post* are largely unchanged. For example, turnover rate of treated group increase by 13 percentage points (see column (1)). The raw return and own-benchmark abnormal return decrease by 1 percentage point following the winning of the IPO allotment (see columns (3) and (4)).

In summary, our main results are largely the same after controlling for person time-invariant factors through person fixed effects.

5.6 Net Wealth Effect of Winning the IPO Allotment

Winning IPO allotment itself increases households' welfare, but the subsequent excessive trading decreases households' welfare. A natural question arises: what the net wealth effect of winning the IPO allotment is? Considering that the RMB-value loss associated with excessive trading should be larger for households with larger portfolio and that the gain from winning the IPO allotment is largely constant across portfolio wealth, we expect the net wealth effect to decrease with households' portfolio wealth.

To formally estimate the net wealth effect, we first divide our sample into 10 decimals based on households' wealth level. Then, for each group, we re-estimate the model reported in column (4) of Table 4 and obtain the coefficient β_1 on *Treat*×*Post*. Finally, the RMB-value net

wealth is defined as the gain from winning the IPO allotment + wealth $\times\beta_1$. The gain from winning the IPO allotment is defined as (shares obtain $\times$(share price at the end of post-event period ─ IPO price). We report the net wealth effect in Table 7.

Consistent with our expectation, the net wealth effect of winning the IPO allotment is decreasing with the household's wealth. For households in the bottom decimal (lowest portfolio wealth), their net wealth effect is around 19 thousand RMB. Such a net wealth effect gradually decreases to around 5 thousand RMB for the 2nd top decimal wealthy group. In contrast, for the ones in the top decimal (the ones with largest portfolio wealth), their net wealth effect is –23 thousand RMB. Such a negative value is because the loss of excessive trading surpass the gain obtained from the IPO shares. Overall, winning the IPO allotment indeed benefits the winner; but the overconfidence following such good luck greatly offset (or even reverse) the gain.

6. Conclusions

Overconfidence is a cognitive bias that is confirmed empirically to predict a wide range of economic outcomes. In this paper, we ask: What makes people overconfident? Does the past experience of good luck make people overconfident about their prospect in the future? Existing literature provides little evidence on this question, possibly because it is empirically to measure "good luck." In this paper, we exploit a natural experiment in China's stock market to examine whether experiencing good luck makes people overconfident. We use the winning of IPO allotment as a measure of "good luck". We find that households who luckily win the IPO allotment subsequently trade more in the stock market and lose more money (a reflection of overconfidence). We also consider alternative explanations such as wealth effect and house money effect; and these

explanations are unlikely to hold. Overall, our results are consistent with the view that experience of good luck makes people overconfident about their prospect in the future.

Our study also has implication on how luck in perceived by human beings in the reality. Do people believe in luck, meaning they tend to view good luck as a stable (at least for a short period of time) and internal attribute which they possess? Or Do people do not believe in luck and instead maintain the rational view that it is external and unreliable (just as modelled in most of the economic and finance literature)? Do people (incorrectly) revise their subjective assessment of luck after experiencing some good luck? Contributing to these debates, our study provides suggestive evidence that people tend to believe in luck and become overconfident about their future luck after recently experiencing lucky events.

Appendix 1: Variable Definitions

Variable	Definition
Turnover1	Min(Buy Volume, Sell Volume)/Average Portfolio Value
Turnover2	(Half of Buy Volume + Half of Sell Volume)/Average Portfolio Value
Portfolio value	Value of total stock holding
Market index	Market return of the Composite in the Shanghai Stock Exchanges
Benchmark return	3-month Holding Return of Beginning of Period Portfolio
Abnormal return	Raw portfolio return – benchmark return

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Table 1: Summary Statistics

The sample consists of 8,285,824 person-period observations from 2014–2016. We obtain data from Shanghai Stock Exchange. Definitions of all variables are provided in Appendix 1. All continuous variables are winsorized at the 1st and 99th percentiles.

	Mean	StdDev	25th Percentile	Median	75th Percentile
Turnover1	431%	567%	69%	213%	549%
Turnover2	394%	558%	39%	176%	504%
Raw portfolio return	11.10%	32.32%	-7.44%	5.45%	25.68%
Own-benchmark abnormal portfolio return	7.07%	32.71%	-12.17%	2.92%	22.13%
Portfolio value (in RMB)	429896.8	1395682	74920.83	164407.87	371269.12
Market return	9.33%	22.58%	5.05%	34.62%	45.42%

Table 2: Univariate Tests

This table reports the univariate tests that examine the impacts of winning the IPO allotment on people's trading behavior. Treated group is the group of people who win the IPO allotment. For each individual in the treated group, we match him to a control individual who did not win the IPO allotment but has the closest portfolio value in the three-month period prior to the IPO subscription. Variable definitions are provided in Appendix 1. All continuous variables are winsorized at the 1st and 99th percentiles. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Treated group (1)	Control group (2)	Difference-in-differences test (t-statistics of t-test: (1)=(2))
△Turnover1	33%	23%	20.82***
△Turnover2	33%	19%	29.84***
△Return	-20%	-19%	28.83***
△Abnormal return	-14.7%	-13.8%	30.87

Table 3: The Effect of Winning IPO Allotment on Turnover

This table reports the difference-in-differences tests that examine the impacts of winning the IPO allotment on people's trading behavior. The indicator variable *Treat* takes the value of one if the person is in the treated group, and zero if the person is the in the control group. The indicator variable *Post* takes the value of one for the three-month period after winning the IPO allotment, and zero for the three-month period before winning the IPO allotment. Variable definitions are provided in Appendix 1. All continuous variables are winsorized at the 1st and 99th percentiles. T-statistics based on robust standard errors clustered by person are in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Turnover1	(2) Turnover1	(3) Turnover2	(4) Turnover2
Treat×Post	0.139***	0.140***	0.098***	0.099***
	(28.26)	(28.38)	(19.53)	(19.68)
Treat	0.142***	0.142***	0.187***	0.187***
	(27.04)	(27.14)	(35.12)	(35.30)
Post	0.196***	0.380***	0.231***	0.437***
	(56.70)	(94.38)	(65.77)	(106.89)
Ln(Wealth)		-0.237***		-0.263***
		(-119.90)		(-130.76)
Market return		0.787***		0.880***
		(81.75)		(90.21)
Constant	3.737***	6.430***	4.073***	7.058***
	(1,014.41)	(265.04)	(1,091.20)	(286.19)
Observations	8,285,824	8,285,824	8,285,824	8,285,824
Adj_R^2	0.1%	0.4%	0.1%	0.5%

Table 4: The Effect of Winning IPO Allotment on Performance

This table reports the difference-in-differences tests that examine the impacts of winning the IPO allotment on people's stock performance. The indicator variable *Treat* takes the value of one if the person is in the treated group, and zero if the person is the in the control group. The indicator variable *Post* takes the value of one for the three-month period after winning the IPO allotment, and zero for the three-month period before winning the IPO allotment. Variable definitions are provided in Appendix 1. All continuous variables are winsorized at the 1st and 99th percentiles. T-statistics based on robust standard errors clustered by person are in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Raw return	(2) Raw return	(3) Abnormal return	(4) Abnormal return
Treat×Post	-0.009***	-0.009***	-0.010***	-0.010***
	(-19.92)	(-25.35)	(-21.73)	(-27.74)
Treat	0.012***	0.012***	0.013***	0.013***
	(37.86)	(46.39)	(40.59)	(50.04)
Post	-0.138***	0.070***	-0.191***	0.013***
	(-413.28)	(259.32)	(-599.08)	(51.71)
Ln(Wealth)		0.006***		0.008***
		(82.07)		(105.88)
Market return		0.891***		0.873***
		(1,748.38)		(1,779.98)
Constant	-0.128***	-0.656***	0.202***	-0.077***
	(-133.51)	(-26.79)	(912.91)	(-83.01)
Observations	8,285,824	8,285,824	8,285,824	8,285,824
Adj_R^2	4.8%	32.5%	9.2%	36.4%

Table 5: Subsample Analysis on Rich Individuals

This table reports the difference-in-differences tests that examine the impacts of winning the IPO allotment on people's trading behavior and portfolio return, based on a group of highly wealthy households. The indicator variable *Treat* takes the value of one if the person is in the treated group, and zero if the person is the in the control group. The indicator variable *Post* takes the value of one for the three-month period after winning the IPO allotment, and zero for the three-month period before winning the IPO allotment. In Panel A, we focus on the subsample of households whose portfolio wealth is in the top 10% of our full sample. In Panel B, we focus on the subsample of households whose portfolio wealth is at least 5 million RMB. Variable definitions are provided in Appendix 1. All continuous variables are winsorized at the 1st and 99th percentiles. T-statistics based on robust standard errors clustered by person are in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Top 10% Wealthy Household

	(1) Turnover1	(2) Turnover2	(3) Raw return	(4) Abnormal return
Treat×Post	0.147***	0.155***	-0.016***	-0.014***
	(9.80)	(10.08)	(-13.25)	(-12.40)
Treat	0.153***	0.160***	0.012***	0.010***
	(9.68)	(9.96)	(14.16)	(12.30)
Post	0.587***	0.685***	0.070***	0.004***
	(48.10)	(54.86)	(82.28)	(5.04)
Ln(Wealth)	-0.225***	-0.223***	0.004***	0.005***
	(-21.72)	(-21.09)	(10.44)	(11.81)
Market return	1.050***	1.090***	0.955***	0.941***
	(36.07)	(36.71)	(581.90)	(599.14)
Constant	6.182***	6.437***	-0.107***	-0.034***
	(41.41)	(42.10)	(-17.49)	(-5.89)
Observations	828,581	828,581	828,581	828,581
Adj_R^2	0.2%	0.4%	36.3%	41.7%

Panel B: Households with Portfolio Wealth Greater than 5 Million RMB

	(1) Turnover1	(2) Turnover2	(3) Raw return	(4) Abnormal return
Treat×Post	0.203***	0.210***	-0.011***	-0.009**
	(4.19)	(4.18)	(-2.64)	(-2.46)
Treat	0.189***	0.201***	0.006**	0.004
	(3.82)	(3.99)	(2.21)	(1.29)
Post	0.715***	0.848***	0.067***	-0.002
	(18.35)	(20.98)	(23.09)	(-0.68)
Ln(Wealth)	-0.252***	-0.248***	0.006***	0.006***
	(-5.69)	(-5.44)	(3.17)	(3.14)
Market return	1.236***	1.233***	0.988***	0.975***
	(13.84)	(13.45)	(184.45)	(191.10)
Constant	6.441***	6.634***	-0.134***	-0.049*
	(9.07)	(9.08)	(-4.36)	(-1.66)

Observations	72,631	72,631	72,631	72,631
Adj_R^2	0.6%	0.7%	39.6%	45.5%

Table 6: Robustness Check: Controlling for Person Fixed Effect

This table reports the difference-in-differences tests that examine the impacts of winning the IPO allotment on people's trading behavior and portfolio return, controlling for person fixed effects. The indicator variable *Treat* takes the value of one if the person is in the treated group, and zero if the person is the in the control group. The indicator variable *Post* takes the value of one for the three-month period after winning the IPO allotment, and zero for the three-month period before winning the IPO allotment. Variable definitions are provided in Appendix 1. All continuous variables are winsorized at the 1st and 99th percentiles. T-statistics based on robust standard errors clustered by person are in parentheses. The superscript ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Turnover1	(2) Turnover2	(3) Raw return	(4) Abnormal return
Treat×Post	0.132***	0.090***	-0.010***	-0.010***
	(26.81)	(18.09)	(-25.84)	(-28.69)
Post	0.109***	0.160***	0.084***	0.022***
	(29.84)	(42.89)	(312.83)	(88.35)
Ln(Wealth)	1.839***	1.829***	-0.010***	0.091***
	(54.94)	(54.16)	(-25.84)	(43.21)
Market return	-0.354***	-0.288***	0.050***	0.912***
	(-44.87)	(-35.92)	(24.43)	(1,619.23)
Constant	-18.300***	-17.835***	0.952***	-1.081***
	(-45.33)	(-43.78)	(1,604.65)	(-42.54)
Person FE	Yes	Yes	Yes	Yes
Observations	8,285,824	8,285,824	8,285,824	8,285,824
Adj_R^2	0.5%	0.4%	36.4%	47.8%

Table 7: Net Wealth Effect of Winning the IPO Allotment

This table reports the net wealth effect of winning the IPO allotment. We divide our full sample into decimals based on portfolio wealth. Based on each group, we re-estimate the model of column (4) of Table 4 and obtain the coefficient on *Treat*×*Post*. Gain from IPO is defined as IPO shares × (share price at the end of post-treatment period ─ IPO price). Wealth loss due to overconfidence is defined as portfolio wealth × the coefficient on *Treat*×*Post*. The net wealth effect is the sum of IPO gain the wealth loss due to overconfidence.

Rank of the 10 portfolio wealth decimal	(1) Gain from IPO	(2) Loss due to overconfidence	(3) Net wealth effect (1)+(2)
1 (lowest portfolio wealth)	19389	-175	19214
2	19245	-297	18948
3	18960	-600	18359
4	18601	-630	17971
5	18156	-1138	17017
6	17514	-1148	16366
7	16864	-2879	13985
8	16066	-3753	12312
9	15290	-9688	5602
10 (highest portfolio wealth)	16163	-39487	-23324