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## ENDOWMENT EFFECTS IN THE FIELD: EVIDENCE FROM INDIA'S IPO LOTTERIES

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## Abstract

Winners of randomly assigned initial public offering (IPO) lottery shares are significantly more likely to hold these shares than lottery losers 1, 6, and even 24 months after the random allocation. This effect persists in samples of wealthy and highly active investors, suggesting along with additional evidence that this type of "endowment effect" is not solely driven by portfolio inertia or wealth effects. The effect decreases as experience in the IPO market increases, but persists even for the most experienced investors. These results suggest that agents' preferences and/or beliefs about an asset are not independent of ownership, providing field evidence derived from the behavior of 1.5 million Indian stock investors which is in line with the large laboratory literature documenting endowment effects. We evaluate the extent to which prominent models of endowment effects and/or investor behavior can explain our results. A combination of inattention and non-standard preferences (realization utility) or non-standard beliefs (salience based probability distortions) appears most consistent with our findings.



JEL Classification: G11, G14, C93, D12

Keywords: endowment effect, exchange asymmetry, reference dependence, loss aversion, salience, inattention, lotteries, causal inference, India



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# Endowment Effects in the Field: Evidence from India's IPO Lotteries*

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June 12, 2016

**Abstract**

Winners of randomly assigned initial public offering (IPO) lottery shares are significantly more likely to hold these shares than lottery losers 1, 6, and even 24 months after the random allocation. This effect persists in samples of wealthy and highly active investors, suggesting along with additional evidence that this type of "endowment effect" is not solely driven by portfolio inertia or wealth effects. The effect decreases as experience in the IPO market increases, but persists even for the most experienced investors. These results suggest that agents' preferences and/or beliefs about an asset are not independent of ownership, providing field evidence derived from the behavior of 1.5 million Indian stock investors which is in line with the large laboratory literature documenting endowment effects. We evaluate the extent to which prominent models of endowment effects and/or investor behavior can explain our results. A combination of inattention and non-standard preferences (realization utility) or non-standard beliefs (salience based probability distortions) appears most consistent with our findings.

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# 1 Introduction

A large and influential laboratory literature documents that the act of owning an object has an important causal effect on the subject's subsequent valuations of the object. These results call into question a basic assumption underlying most neoclassical economic theory that preferences and beliefs are independent of ownership, and have resulted in the development of new theoretical ideas to explain the laboratory evidence (Thaler, 1980; Kőszegi and Rabin, 2006; Bordalo et al., 2012). An important challenge for this area of work is the extent to which such "endowment effects" manifest themselves in market settings outside the laboratory, and if they do, whether they can be explained by the new theoretical models. Two particular reasons to heed caution in extrapolating from lab experiments documenting endowment effects to markets outside of the lab are that (1) market participants are likely to have more relevant experience than laboratory subjects, and (2) findings of endowment effects in the lab appear to be sensitive to experimental procedures, rendering it difficult to determine which experimental procedures map most closely to markets outside of the laboratory (Zeiler and Plott, 2004).

List (2003) and List (2011) are two recent studies that move outside the lab to test for endowment effects, using a field experimental design with sports memorabilia and collectible pin traders as subjects. Traders are randomly assigned to own one of two pieces of sports memorabilia or collector's pins, and subsequently given the opportunity to trade the objects in the marketplace. Given the random assignment, trading rates of less than 50 percent constitute evidence of endowment effects. Both studies find substantial endowment effects amongst inexperienced traders, but strongly attenuated endowment effects amongst the most experienced participants.[1] The latter result is provocative, because it suggests that the ample evidence on endowment effects from lab experiments has limited relevance in market settings

[1]The main difference between these two studies is that List (2011) induces experimental variation in the level of experience traders have (by randomly encouraging trade and then conducting the endowment experiment one year later), while List (2003) uses the naturally occurring variation in experience (i.e., whether a trader is a dealer in the market or has made many trades prior to the experiment).

outside the lab, which may be populated by experienced participants.[2]

The research design employed in List (2003) and List (2011) is appealing because it embeds a field market setting (i.e., traders in a naturally occurring market) within an experimental design that allows for the clean estimation of endowment effects. But the desire to maintain experimental control whilst simultaneously operating in the field naturally limits the scope (in terms of markets studied) and size (in terms of subjects) of these particular field experiments – they focus on two specialized markets and use small samples (between 60 and 74 subjects per experiment). While these limitations do not threaten the internal validity of these studies' conclusions, it is difficult to judge whether the results from these specific markets can be generalized to many important markets where we might expect endowment effects to operate.[3]

In this paper, we broaden the scope of field tests of endowment effects, exploiting a natural experiment that provides randomized variation in endowments to millions of market participants outside of the lab. As a result of regulatory requirements, in many cases Indian initial public offering (IPO) shares are randomly assigned to applicants. Under the assumption of minimal wealth effects (which we discuss in detail later), winners and losers in these IPO lotteries should have virtually identical preferences, beliefs, and information sets before and after the shares are allotted. While lottery losers do not have the opportunity to buy the shares at the IPO issue price, once the stock begins to trade freely, both winner and loser

[2]We emphasize the List (2003) and List (2011) studies because they involve traders making decisions regarding the naturally occurring good in the relevant marketplace (e.g. decisions about baseball cards at a sports memorabilia show). Other relevant studies, which integrate lab and field procedures, include List (2004), who finds endowment effects in the decision to trade or hold randomly assigned chocolate bars or mugs amongst inexperienced (but not among experienced) attendees at a sports memorabilia show. A related literature tests whether endowment effects can be harnessed to improve the effectiveness of incentives, assigning a control group a standard incentive to be paid after a good performance, and a treatment group an upfront incentive that is taken away if performance is poor. Hossain and List (2012) and Fryer Jr et al. (2012) find this framing of incentives improves manufacturing worker and teacher performance respectively, while Levitt et al. (2012) finds no effect of this type of framing of test score contingent payments on student test scores. These results suggest the relevance of endowment effects in the field, but may be less relevant for endowment effects in product and asset markets.

[3]As List (2011) notes, the small sample sizes also cause relatively large confidence intervals around the endowment effect estimates, making it difficult to pinpoint the amount by which experience attenuates the endowment effect.

groups have equal opportunities to trade the stock. Given the equivalence of information sets and background characteristics induced by the random assignment, we should expect that the holdings of this randomly allocated stock across the two groups should converge rapidly over time. If endowment effects are important, however, we should expect a divergence in the behavior of the randomly chosen winners and losers.[4]

We document that the winners of IPO lotteries are substantially more likely to hold the randomly allocated IPO shares for many months and even years after the allocation. In our main results, we find that 62.4 percent of IPO winners hold the IPO stock at the end of the month after listing, while only 1 percent of losers hold the stock. Six months after the lottery assignment the gap decreases slightly, to 46.6 percent of winners holding the stock and 1.6 percent of the losers holding the stock, but even 24 months after the random assignment we find that winners are 35 percentage points more likely to hold the IPO stock than losers. We term this effect an "endowment effect," with analogies to the laboratory literature, because the fact that winners of these lotteries are randomly endowed with the IPO stock appears to cause them to be more likely to hold stock than losers.

We investigate whether this endowment effect attenuates substantially for the most experienced traders in our setting, as in List (2003). We compare the strength of this endowment effect across investors with different levels of experience in the IPO market measured in a number of different ways. For example, for each investor, we observe the number of IPOs they have previously been allotted over the past 10 years, a measure of experience which varies from 0 previous experiences up to 30 previous experiences at the $90^{th}$ percentile of the distribution. Consistent with List (2003), we find a strong negative correlation (which is robust to the inclusion of various controls) between this experience measure and the difference in holdings between lottery winners and losers. However, while List (2003) finds that endowment effects become negligible amongst his sample of experienced traders (sports

[4]Throughout the paper we refer to the difference in propensity to hold the IPO stock across IPO winners and losers as an endowment effect, to be consistent with most of the laboratory literature which refers to this type of exchange asymmetry as an endowment effect. We do not use the term endowment effect to suggest any particular theoretical mechanism underlying our empirical findings.

card dealers and very experienced non-dealers), we find substantial endowment effects even amongst investors who have participated in over 30 IPOs – on average these highly experienced winners still hold 27 percent of their lottery allotments at the end of the month of randomly receiving the IPO, while losers hold 7 percent of the initial allocation.[5,6]

We next explore the extent to which prominent theories of endowment effects and/or investor behavior can explain our empirical results.[7] Theories in the first category (the "standard expected utility" category) assume that individuals have preferences and beliefs that are independent of endowments, but explore whether some other feature of the setting (e.g., wealth effects or inertial behavior) could cause IPO winners to prefer greater holdings of the IPO stock. Theories in the second category consider the role of preferences where endowments directly affect valuations (e.g., reference dependent preferences with loss aversion), or the possibility that endowments might affect agents' beliefs (e.g., salience-based probability distortions). While the lab literature has attempted to completely rule out certain mechanisms while testing for the presence of others, we note that in our field setting (and very likely in most field settings) various mechanisms from both categories could be at play, and decisively identifying a single theoretical explanation of our results would require additional experimental variation. Our focus is on applying each theory to our empirical setting, deriving testable predictions, and then evaluating whether our major empirical facts are consistent with those predictions.

We provide a comprehensive discussion of issues pertaining to the first category of explanations later in the paper, but note two major examples of such features here, namely,

[5] These results are also interesting in light of Haigh and List (2005), who find that professional futures traders exhibit greater myopic loss aversion and raise the possibility that market experience might exacerbate behavioral anomalies. Our evidence rejects the idea that more experienced market participants exhibit the endowment effect anomaly more strongly.

[6] We also exploit the random assignment of previous lotteries to provide a sharper comparison of whether the behavior of more experienced lottery players converges more than that of less experienced lottery players, and find evidence that those who have previously won IPOs have smaller estimated endowment effects in the future. Similar to the experience correlations discussed above, however, the rate of learning appears to be slow. Overall, the evidence from these two types of analyses suggests that while experience does substantially reduce this particular endowment effect, it seems unlikely that experience eliminates this anomaly completely.

[7] See Ericson and Fuster (2014) for a review of laboratory experiments that estimate the endowment effect and attempt to distinguish causal mechanisms.

wealth effects and inertial behavior. The winners in our experiment receive a wealth shock since Indian IPOs are typically under priced relative to the first price at which they trade on the market. However, we argue that the magnitude of this shock is unlikely to explain the divergence in winner-loser holding patterns for a number of reasons. Most importantly, the actual gains in the treatment IPO (on average US$ 62) are small relative to the amount of cash participants are required to place in escrow in order to participate in these lotteries in the first place (on average US$ 1,750), making it unlikely that lottery winnings are relieving a major wealth constraint. Moreover, we find that endowment effects are similar for IPOs associated with low and high wealth shocks (i.e., the listing return on the IPO).

Inertial behavior by investors is a second potentially important explanation for our results, involving no effect of endowments on valuations or beliefs. (S,s) models of optimal inaction in the presence of fixed costs have been studied in the economics literature for many decades. In our setting, such fixed costs might include brokerage commissions, transactions costs, taxes, or cognitive processing costs such as the cost of accessing accounts and placing trades.[8] Given that our main results (that lottery winners tend to hold the stock while losers do not) comes from inaction on the part of investors in the IPO stock, inertia is naturally a good description of their behavior. It is important, however, to draw a distinction between inertial behavior that is specific to the IPO stock, and inertial behavior affecting behavior in the portfolio as a whole. If our results are due to the fact that investors are inert in their entire portfolios, this would obviously reduce the relevance of our study to other settings where endowment effects may be present. However, if the inertial behavior is specific to the IPO stock, it is interesting to further evaluate models of preferences, beliefs, or information that might generate the endowment effects that we observe.

A number of facts suggest that inertial behavior at the portfolio level is unlikely to generate the endowment effects we observe. First, we find a large endowment effect even

[8]Recent papers have attempted to characterize optimal decision rules in the presence of both standard fixed costs and information processing costs – see, for example, Alvarez et al. (2013) and Abel et al. (2013). Andersen et al. (2015) attempt an empirical characterization of both inattention and inertia using Danish households' mortgage refinancing decisions, and find that both are important factors.

when we restrict our sample to those winners and losers who make more than 20 trades (in non-IPO stocks) in each of the months in which we measure the effect. Thus, the results are not being driven by a subset of investors who are mainly inactive.[9] Second, when we further restrict the sample to winners and losers who recently made a trade (in non-IPO stocks) of sizes less than or equal to the size of the initial random endowment of the IPO, we find that our point estimate of endowment effect is very similar, suggesting that our results are not being driven by the IPO position being "too small" to warrant action. Finally, in related work we find that lottery winners have a higher trading intensity (of the non-IPO stocks in their portfolio) than lottery losers, and tend to tilt their portfolios in the direction of the industry sector in which the IPO stock is situated, suggesting that winning the lottery appears to reduce the (cognitive) transaction costs associated with making trades (Anagol et al., 2015).

Turning to the second category of explanations, we consider a series of theoretical models that have either been prominent explanations of endowment effects or of related investor behavior (such as the disposition effect) in past work. Our goal is not to conclusively determine which model explains all of our empirical facts, but instead, to provide guidance for future empirical work that tests theoretical mechanisms that might drive endowment effects in the field.

Amongst endowment effect explanations where endowments do have a causal effect on valuations, the most prominent mechanism explored in the literature is the idea that agents have reference dependent utility with loss-aversion. In this framework agents receive utility from potential transactions relative to a reference point, with the particular form of the reference point having an important impact on predicted behavior. Kőszegi and Rabin (2006) (KR) present a theory where the reference point is set by an agent's recently formed expectations about future outcomes, and we consider three models in this class. These

[9]This finding also assuages concerns that our results are being driven by "trade uncertainty"– the idea that investors are uncomfortable with trading in general and therefore stick to the status quo (Engelmann and Hollard, 2010).

models contain increasingly complex formulations of the reference point, culminating in a setup which more closely matches features of our real-world experimental environment. In each case, we find the range of parameter values (for the extent of loss aversion, the expected return on the stock, and the expected probability of winning the IPO lottery) where the same agent would choose to hold the stock if they won the lottery, but not purchase the stock if they lost the lottery.[10] We discuss these models in detail in the paper and the Appendix, but, in general, find that they deliver narrow parameter ranges in which the endowment effect plan is a PE, or generate auxiliary predictions that are not supported by the data.

We next consider a number of alternative models including the "aversion to bad deals" model of Weaver and Frederick (2012), the realization utility model of Shefrin and Statman (1985) and Barberis and Xiong (2012), and the salience model of Bordalo et al. (2012). The bad deals and realization utility models can generate an endowment effect; however, both models deliver the prediction that the size of the endowment effect varies inversely with the size of the initial listing gain on the IPO stock. This prediction is strongly refuted by the data, where we find that the largest endowment effects occur for IPOs with closer to zero gains, with smaller endowment effects observed in IPOs with either negative or highly positive listing gains.

We find that the salience model of Bordalo et al. (2012) is able to plausibly generate the behavior of winners post-listing. However, once we embed salience-based decision making in a more realistic setup which includes the initial application lottery, we find that it is unable to generate the endowment effect that we see, primarily because the model (as well as many of the other models that we consider) is unable to provide an explanation for why lottery *losers* consistently choose *not* to purchase the stock on the open market.[11] To explain this

[10] In the language of Kőszegi and Rabin (2006), we find the range of parameter values where we would observe an endowment effect in our experiment because agents are playing their "personal equilibrium" strategies. In several cases, we also consider whether the plan generates the highest expected utility of all possible PE plans, i.e., whether it is a "preferred personal equilibrium" or PPE.

[11] We note that this is a new fact to add to the broad literature on the disposition effect – this is primarily because this literature has not thus far been able to observe a "control" group of investors with similar background characteristics that did not own the stock.

feature of the data, we discuss a simple model of attention allocation in which lottery losers are assumed to be completely inattentive to the stock, post-lottery. One possible micro foundation for this assumption is that winning the stock in the lottery provides "exposure" to the stock, which keeps it in the attention set of winners; but since losers do not receive this exposure, it remains out of the attention set for them (see, for example, Bordalo et al. (2015)). Overall, we conclude that it will require a combination of the features present in the different models we consider in order to provide a fuller explanation of the rich set of facts that we uncover in our natural experiment.

# 2 The Experiment: India's IPO Lotteries

As with many other details of regulation in the country, the Indian regulatory process for IPOs is quite complex. Several papers (e.g., Anagol and Kim, 2012; Campbell et al., 2015) have used this complexity of the Indian regulatory process to cleanly identify a range of economic phenomena. Our experiment uses the Indian retail investor IPO lottery as a naturally occurring setting in which some agents are randomly endowed with an asset while others are not, and we can observe agents' choices to trade the asset following the random endowment. In this section we describe the circumstances in which these lotteries occur (including a specific example), and in the next section describe how they can be used to estimate endowment effects. We provide the precise details of the IPO lottery process and associated regulations in Appendix Section A.1.

To summarize, these IPO lotteries arise in situations in which an IPO is oversubscribed, and the use of a proportional allocation rule to allocate shares would violate the minimum lot size of shares set by the firm. In these situations, the lottery is run to give investors who applied for shares their proportional allocation *in expectation*. The outcome of the lottery is that some investors who applied receive the minimum lot size (this is the treatment group), while others who applied receive zero shares (the control group). The fundamental reason for the lottery is that in India, regulations require that a firm must set aside 30% or 35% of its shares (depending on the type of issue) to be available for allocation to retail investors at the time of IPO. For the purposes of the regulation, "retail investors" are defined as those with expressed share demands beneath a preset value. At the time of writing, this preset value is set by the regulator at Rs. 200,000 (roughly US $3,400); this value has varied over time (see Appendix Section A.1).

The share allocation process in an Indian IPO begins with the lead investment bank, which sets an indicative range of prices. The upper bound of this range (the "ceiling price") cannot be more than 20% higher than the lower bound (or "floor price"). Importantly, a minimum number of shares (the "minimum lot size") that can be purchased at IPO is also determined at this time. All IPO bids (and ultimately, share allocations) are constrained to be integer multiples of this minimum lot size.

Retail investors can submit two types of bids for IPO shares. The simplest and most frequent type of bid is a "cutoff" bid, where the retail investor commits to purchasing a stated multiple of the minimum lot size at the final issue price that the firm chooses within the price band.[12] To submit the bid, the retail investor deposits an amount into an escrow account, which is equal to the ceiling of the price band multiplied by the desired number of shares. If the investor is allotted shares, and the final issue price is less than the ceiling price, the difference between the deposited and required amounts is refunded to the investor. The remaining investors in our sample submitted "full demand schedule" bids, i.e., the number of lots that they would like to purchase at each possible price within the indicative range, once again depositing in escrow the maximum monetary amount consistent with their demand schedule at the time of submitting their bid, with a refund processed for any difference between the final price and the amount placed in escrow.

Once all bids have been submitted the total levels of demand and supply of shares are set (see Appendix Section A.1 for additional details), and regulation determines how shares

[12] 93% of applicants in our sample submit cut-off bids.

will be allotted in the case that demand exceeds supply.

We define retail over subscription $v$ as the ratio of total retail demand for a firm's shares to total supply of shares by the firm to retail investors, i.e., the total number of shares made available by the firm for retail investors to purchase.

There are then three possible cases:

1. $v \leq 1$. In this case, all retail investors are allotted shares according to their demand schedules.

2. $v > 1$, and shares can be allocated to investors *in proportion to their stated demands without any violation of the minimum lot size constraint*. There is no lottery involved in this case.

3. $v >> 1$ (the issue is substantially oversubscribed), and a number of investors under a proportional allocation scheme would receive an allocation which is lower than the minimum lot size. This constraint cannot be violated by law, and therefore, all such investors are entered into a lottery. In this lottery, the probability of receiving the minimum lot size is proportional to the number of shares in the original bid and lottery applicants receive their proportional allotment in expectation.[13]

This third case, in which the lottery takes place, provides the random variation that we exploit to test for the endowment effect. Far from being an unusual occurrence, in our sample alone (which is a subset of all IPOs in the Indian market over the sample period), roughly 1.5 million Indian investors participate in such lotteries over the 2007 to 2012 period in the set of 54 IPOs that we study.

The time line of the application and allotment process is as follows. Applications are received over a two-day period termed the "subscription period." Shares are allotted to the winner's accounts approximately 12 days after the applications are received. The shares

[13] Appendix Section A.3 shows a mathematical derivation of the probabilities of winning allotments based on the level of excess demand.

typically list approximately 21 days after the subscription period. Refunds of the escrow amounts begin to be processed after the allotments are made, usually 14 days after the allotments are made, so it is possible that the refunds are made after the shares are listed (we discuss how this might affect our inferences later). Lottery losers receive a complete refund on their escrow amounts.

## 2.1 An Example: Barak Valley Cements IPO Allocation Process

Barak Valley Cements' IPO opened for subscription on October 29, 2007, and remained open for subscription through November 1, 2007. The stock was simultaneously listed on the National Stock Exchange (NSE) and the Bombay Stock Exchange (BSE) on November 23, 2007. The listing price of the stock was Rs. 42 per share, and the stock closed on the first day of listing at Rs. 56.05 per share, for a 33.45% listing day gain. The retail over subscription rate $v$ for this issue was 37.62. Given this high $v$, all retail investors that applied for this IPO were entered into a lottery.

Table 1 shows the official retail investor IPO allocation data for Barak Valley Cements.[14] Each row of column (0) of the table shows the share category $c$, associated with a number of shares applied for given in column (1), which, given the minimum lot size $x = 150$ for this offer is just $cx$. In this case, the total number of share categories ($C$) equals 15, meaning that the maximum retail bid is for 2,250 shares. This is because $C = 16$ would give a number of 2,400 shares, and a maximum subscription amount of Rs. 100,800 at the listing price of Rs. 42. This maximum subscription amount would violate the prevailing (in 2007) regulatory maximum retail investor application constraint of Rs. 100,000 rupees per IPO. Column (2) of the table shows the total number of retail investor applications received for each share category, and column (3) is simply the product of columns (1) and (2).

Column (4) shows the investor allocation under a proportional allocation rule, i.e., $\frac{cx}{v}$. The proportional allocation rule would yield $v = 37.62$, which is less than the firm's minimum

[14] These data are obtained from `http://www.chittorgarh.com/ipo/ipo_boa.asp?a=134`.

lot size of 150 shares per investor for all share categories. By regulation, the firm is now required to conduct a lottery to decide share allocations.

Column (5) shows the probability of winning the lottery for each share category $c$, which is $p = \frac{c}{v}$. For example, 2.7% of investors that applied for the minimum lot size of 150 shares will receive this allocation (this is the treatment group in this share category), and the remaining 97.3% of investors applying in this share category (the control group) will receive no shares. In contrast, 40.6% of investors in share category $c = 15$ receive the minimum lot size $x = 150$ shares. For this particular IPO, *all* retail investors are entered into a lottery, and ultimately receive either zero or 150 shares of the IPO.

Column (6) shows the total number of shares ultimately allotted to investors in each share category, which is the product of $x$, column (2), and column (5). Columns (7) and (8) show the total sizes of the treatment and control groups (number of retail investors) in each share category for the Barak Valley Cements IPO lottery, respectively. Across all share categories, 12,953 investors are treated and 55,669 are in the control group.

It is perhaps easiest to think of our data as comprising a large number of experiments, in which each experiment is a share category within an IPO. *Within* each experiment the probability of treatment is the same for all applicants, and we exploit this source of randomness, combining all of these experiments together to estimate the average causal effect of winning an IPO lottery on future holdings of the IPO stock. We explain this more fully in the methodology section, following the data description below.

## 2.2 Data

When an individual investor applies to receive shares in an Indian IPO their application is routed through a registrar. In the event of heavy over subscription leading to a randomized allotment of shares, the registrar will, in consultation with one of the stock exchanges, perform the randomization to determine which investors are allocated. We obtain data on the full set of applicants to 85 Indian IPOs over the period from 2007 to 2012 from one of

India's largest share registrars. 54 of these IPOs had at least one randomized share category. This registrar handled the largest number of IPOs by any one firm in India since 2006, covering roughly a quarter of all IPOs between 2002 and 2012, and roughly a third of all IPOs over our sample period.

For each IPO in our sample, we observe whether or not the applicant was allocated shares, the share category $c$ for which they applied, the geographic location of the applicant by pincode,[15] the type of bid placed by the applicant (cutoff bid or full demand schedule), the share depository in which the applicant has an account (more on this below), whether the applicant was an employee of the firm, and other application characteristics such as whether the application was supported by a blocked amount at a bank.[16]

Our second major data source allows us to characterize the equity investing behavior of these IPO applicants (and in particular their trading decisions regarding the IPO stock). We obtain these data from a broader sample of information on investor equity portfolios from Central Depository Services Limited (CDSL). Alongside the other major depository, National Securities Depositories Limited (NSDL), CDSL facilitates the regulatory requirement that settlement of all listed shares traded in the stock market must occur in electronic form. CDSL has a significant market share – in terms of total assets tracked, roughly 20%, and in terms of the number of accounts, roughly 40%, with the remainder in NSDL. While we do also have access to the NSDL data (these data are used extensively and carefully described in Campbell et al., 2014), we are only able to link the CDSL data with the IPO allocation information, as we describe below.

The sensitive nature of these data mean that there are certain limitations on the demographic information provided to us. While we are able to identify monthly stock holdings

[15]Pincodes in India are postal codes managed and administered by the Indian Postal Service department of the Government of India. They are similar to zipcodes in the US, although they cover a larger geographical region in India.

[16]An application supported by blocked amount (ASBA) investor is one who has agreed to block the application money in a bank account which will be refunded should she not be allocated the shares in an IPO. The alternative is paying by cheque, i.e., in either case, the money is placed in escrow prior to the allotment process, but in the case of ASBA, any refunds are processed a few days faster.

and transactions records at the account level in all equity securities in CDSL, we have sparse demographic information on the account holders. The information we do have includes the pincode in which the investor is located and the type of investor – accounts are classified as beneficial owners, domestic financial institutions, domestic non-financial institutions, foreign institutions, foreign nationals, government, or retail accounts. This paper studies only the category of retail accounts, as the IPO lottery only applies to this group of investors.

In order to match the application data to the CDSL data on household equity portfolio choice, we obtain a mapping table between the anonymous identification numbers of household accounts from both data sources. We verify the accuracy of the match by checking common geographic information fields provided by both data providers such as state and pincode.[17]

Every applicant for an IPO must register to open (or already have) an account with either of the two depositories (CDSL and NSDL), as the option to receive allocated shares in an IPO in physical form does not exist. For all applicants with accounts in CDSL, we observe accounts that applied for an IPO and were allotted in the lottery, i.e., the treatment group, as well as those that applied, but due to randomized allocation did not get allocated any share in an IPO (the control group).

All CDSL trading accounts are associated with a tax related permanent account number (PAN), and regulation requires that an investor with a given PAN number can only apply once for any given IPO.[18] Thus no investor account may simultaneously belong to both the control and treatment group, or be allocated twice in the same IPO. However, it is possible that a household with multiple members with different PAN numbers could submit multiple applications for a given IPO in an attempt to increase the household's likelihood

[17]We are able to match 99.5 percent of our IPO lottery applicants to our data on portfolio holdings.

[18]In July 2007 it became mandatory that all applicants provide their PAN information in IPO applications. (SEBI circular No.MRD/DoP/Cir-05/2007 came into force on April 27, 2007. Accessed at http://goo.gl/OB61M2 on 19 September 2014.) We confirm there are no violations of this regulation in our data, by checking across all brokerage accounts associated with the anonymized tax identification number of each investor.

of treatment. While we do not directly control for this possibility, we do not believe that this is likely to materially affect our inferences, as we discuss in more detail in the Section covering potential explanations of our results.

Appendix Figure A.7.1 shows the coverage of IPOs in our sample relative to that in the universe of IPOs. Our sample coverage closely tracks aggregate IPO waves, with a severe decline in 2009, and high numbers of IPOs in 2008 and 2010. In our sample of 85 IPOs, 54 IPOs have at least one share category with a randomized lottery allocation, compared to the universe of 176 IPOs with randomized allocations over the period. Appendix Table A.7.1 presents summary statistics on the 54 IPOs with randomized allotments in our sample. The table shows that these IPOs account for 22% of all IPOs over this period by number, and US$ 2.65 BN or roughly 8% of total IPO value over the period, varying from a low of 0.72% of total IPO capital in 2009 to a high of roughly 25% in 2011.

Between 32% and 35% of shares in these IPOs are allocated to retail investors who are not employees of the IPO firm.[19] The average IPO in our sample is 12 times oversubscribed, and we observe a total of 383 randomized share categories (or experiments) across 54 IPOs. These IPOs, and more broadly IPOs in India, under perform in the long run, in a manner consistent with the patterns and trends documented widely in the literature (see Appendix Figure A.7.2). When appropriately adjusted for per-capita GDP differences between the US and India, the account value distribution for the universe of investors in the CDSL data and the lottery sample, are similar to those in the US (see Appendix Figure A.7.3 (a)). While the number of investors who undertake only one trade in the sample is higher in India than in the US, the distribution of trading activity is very similar across the two samples except at the tails (see Appendix Figure A.7.3 (b)).

[19]This is slightly below the mandatory 35% allocation to retail investors because we do not include employees in this calculation as employees are not randomly assigned shares. For further details, refer to the Appendix Section A.1.

## 2.3 Using IPO Lotteries to Estimate Endowment Effects

We estimate endowment effects by comparing the tendency of lottery winners to continue to hold a stock that they were randomly assigned to the tendency of lottery losers to begin to hold a stock they randomly did not receive. It is important to clarify what exactly our lottery winners are endowed with relative to our lottery losers. Table 2 characterizes the application and allotment experience the investors in our analysis received upon being randomly chosen to receive IPO shares. Column (1) of the table shows the mean across all investors in the treatment groups of IPOs in our 383 share category experiments for each of the variables listed in the row headers.[20] Columns (2) through (6) present the percentile of each variable in terms of the distribution across all of the experiments.[21]

On average, both lottery winners and losers put 1,750 dollars into an escrow account to participate in the lottery (row 1, Table 2). Lottery winners receive an average of 150 dollars worth of the IPO stock in the IPO lottery (row 3). They also receive an instant gain of 62 dollars on average, because IPO stocks' listing price is 39 percent higher than the issue price on average (row 5). Lottery losers cannot purchase the stock at the issue price, so the total endowment that the winners receive (which the losers do not) is 212 dollars (150 + 62) of the IPO stock. Both winners and losers get refunds from their escrow accounts of approximately 1,600 and 1,750 dollars, respectively. Once the stock has started trading, both winners and losers are free to trade the stock.

Our approach to estimating endowment effects has important similarities as well as some differences with the two major laboratory methods that have been used. The assignment of treatment is similar to the "valuation paradigm" methodology; experiments in this paradigm randomly assign subjects to owning or not owning an object, and then survey the subjects on their valuation of that object. The key result is that sellers typically report higher

[20] The means are calculated across share categories using the same weighting scheme implied in our regression based comparison of treatment and control means. See Section 3 for details.

[21] We first calculate the mean within each experiment, and then report the corresponding percentile across the experiments. For example, the median share category experiment had a mean application amount of 792 dollars (first row of Table 2).

valuations than buyers (the so called willingness to accept - willingness to pay or WTA-WTP gap).[22] Our setting parallels this method, in the sense that winners of the IPO lotteries are randomly assigned to own the stock, whereas losers are randomly assigned to not own the stock. This randomization ensures that there should not be preference or belief based reasons why winners should value the stock more than losers. Also similarly to these valuation experiments, winners receive a wealth effect when they are endowed with the IPO stock, since winners are allowed to purchase the IPO stock at the issue price and then sell it at the listing price.[23] Since it is not possible for the lottery losers to purchase the stock at the issue price, this constitutes a wealth gain (or loss) that is not available to lottery losers.[24] This literature has typically argued that the wealth effects of assigning a consumer good (typically, a mug or a pen) are small relative to the subject's wealth, and are therefore unlikely to drive their results. Our arguments regarding wealth effects are similar, in that the gains on the lottery shares are most likely small relative to household wealth, and additionally, small relative to the escrow amount that households put in place to participate in the IPO allocation process to begin with. We discuss this issue in more detail in Section 4.

A major difference between our design and experiments in the valuation paradigm is that we infer how subjects value the endowment based on their actual trading decisions, as opposed to surveying investors regarding their valuation of the stock. If there is a large divergence in whether winners or losers hold the stock, this suggests valuation differences across the two groups (assuming negligible wealth and transaction cost effects, which we investigate later). In this sense, our approach is similar to the "exchange paradigm" methodology (see, for example, Engelmann and Hollard (2010)), where laboratory subjects are randomly

[22] For a review see Ericson and Fuster (2014), and for early papers using this method see Knetsch and Sinden (1984), Heberlein and Bishop (1986), and Kahneman et al. (1990).

[23] We refer to the first price the IPO stock trades at on the market as the "listing" price.

[24] The wealth gain in our setting is not equal to the total amount of the endowment because our lottery losers receive a refund equal to the amount of the allotted stock (valued at the issue price). The differential wealth gain to winners versus losers is therefore just the gain in the value of the allotted stock based on the listing return of the stock (62 dollars on average, as described above).

assigned good A or good B, and then later asked if they want to trade. The extent to which the holdings depart from equal proportions in groups randomly assigned goods A and B to begin with provides a quantitative estimate of the endowment effect. The logic here is that after getting the opportunity to trade, both groups should contain equal proportions of owners of goods A and B - just as in our setting, winners and losers should contain equal proportions of IPO stockholders.

In addition to being based in a market setting outside the laboratory, our natural experiment design also avoids four specific laboratory features that have been highlighted as spuriously producing endowment effects in Zeiler and Plott (2004): 1) the endowed object is placed physically in front of the subject, and therefore endowed subjects might gain more information about the endowed versus non-endowed object 2) the endowed object is called a "gift" 3) the procedure measuring the willingness to accept and willingness to pay is not properly incentivized, and 4) the subject is not guaranteed anonymity when making choices. In our setting, 1) lottery winners do not have access to any information about the IPO security that lottery losers cannot obtain through publicly available sources; 2) there is little reason to believe winners would frame receiving the IPO stock as a gift given they put down large escrow amounts to apply for the shares and have to pay the issue price; 3) we measure the endowment effect by measuring the actual divergence in holdings of the IPO stock, which investors are clearly incentivized to choose optimally; and 4) the anonymous nature of financial markets makes it unlikely that investors are concerned about others observing their choices.

# 3 Documenting the Endowment Effect

Our empirical analysis begins by documenting the rate of ownership of the endowed IPO stock across our lottery losers and winners over time. We view each randomized share category in each IPO as a separate experiment with a different probability of being allotted shares. The idea of our empirical specification is to pool all of these experiments in order to maximize statistical power, while ensuring that we exploit only the randomized variation of winning status within each IPO share category.

For example, one of our tests checks whether lottery winners are more likely than losers to hold the IPO stock at the end of the month in which the IPO was listed on the exchange. To do so, we employ the account holdings at the end of the listing month for all applicants in our 383 share category experiments to construct an indicator for holding the IPO stock at the end of the listing month. We then regress this on a treatment indicator and a fixed effect for each separate experiment. These experiment-level fixed effects ensure that our identification of the treatment effect of winning the lottery stems solely from the random variation in treatment *within* each experiment.[25]

More generally, we estimate the causal effect of the experience of winning an IPO lottery on various measures of holdings of the IPO stock for each (event) month $t$, by estimating cross-sectional regressions of the form:

$$y_{ijc} = \alpha + \rho I_{\{success_{ijc}=1\}} + \gamma_{jc} + \epsilon_{ijc}. \tag{1}$$

Here, $y_{ijc}$ is an outcome variable of interest (for instance, an indicator for whether the account holds the IPO stock) for applicant $i$ in IPO $j$, share category $c$. $I_{\{success_{ijc}=1\}}$ is an indicator variable that takes the value of 1 if the applicant was successful in the lottery for IPO $j$ in category $c$ (investor is in the winner group), and 0 otherwise (investor is in the loser group). $\rho$ are the estimated treatment effects in each event-month $t$. $\gamma_{jc}$ are fixed effects associated with each experiment, i.e., each IPO share category in our sample. Angrist et al. (2013) refers to these experiment-level fixed effects as "risk group" fixed effects. Conditional on the inclusion of these fixed effects, variation in treatment is random, meaning that the

[25]See Chapter 3 of Angrist and Pischke (2008) for a discussion of how regression with fixed effects for each experimental group identifies the parameter of interest using only the experimental variation. Our strategy is similar to that employed in Black et al. (2003), who estimate the impact of a worker training program that was randomly assigned within 286 different groups of applicants and Gelber et al. (2015) who study the impact of summer youth employment which is randomized by lotteries within job providers.

inclusion of controls should have no effect on our point estimates of $\rho$. We run this regression separately for different months after the IPO stock is allotted (i.e., we run one of these cross-sectional regressions for the month after the IPO was allotted, another for two months after the IPO was allotted, and so on.)

Angrist (1998) shows that our estimated treatment effect $\rho$ is a weighted average of the treatment effects from each separate share category experiment. In particular, the weights are constructed as:

$$w_c = \frac{r_c(1-r_c)N_c}{\sum_{k=1}^{383} r_k(1-r_k)N_k} \tag{2}$$

where $r_c$ and $N_c$ are the probability of treatment and sample sizes in share category $c$, and we have a total 383 share category experiments. Intuitively, the regression weights give more importance to experiments in which the probability of treatment is closer to $\frac{1}{2}$, and experiments with larger sample sizes – i.e., experiments in which there are many accounts in both treatment and control groups. This weighting scheme implies that our regression estimate exploits purely random variation in treatment induced by the lotteries, since treatment versus control comparisons are only performed *within* share categories, and since $\rho$ is simply a weighted average of these share-category-specific effects.

**Randomization Check.** Table 3 presents summary statistics and a randomization check comparing our lottery winner (treatment) and lottery loser (control) groups. Columns (1) and (2) present the means of variables listed in the row headers in treatment and control groups respectively, and Column (3) presents the difference across the two samples with ***, **, and * indicating statistically significant differences at the 1%, 5%, and 10% levels.[26] All of these variables are measured the month before allotment of the treatment IPO. If the allocation of IPO shares is truly random, we would expect few statistically significant differences across winner and loser groups prior to the assignment of the IPO shares. Column (4) calculates the percent of our 383 share category experiments in which the treatment and

[26] These means are calculated using the weights defined in equation (2), which are the same weights that our main estimating equation uses to combine the share category by share category experimental results in to one treatment effect estimate.

control groups were significantly different at the 10% level. Under the null hypothesis that treatment status is random, we expect that roughly 10% of these experiments will exhibit a significant difference at the 10% level.

The first variable we check for balance on is whether accounts that won the current lottery were also more likely to have been successful in receiving IPO shares in the past. If it was possible to "game" the lottery and increase one's probability of winning we would expect current winners to also have been more successful in the past.[27] Table 3 shows that virtually identical fractions (38%) of both treatment and control investors applied to an IPO with our registrar, or were allotted shares in an IPO not covered by our registrar, in the month prior to treatment.

The next few rows of Table 3 present summary statistics on the application characteristics of control and treatment investors. As mentioned earlier, 93% of these investors submitted an application with a "cutoff" bid, and 4% used ASBA rather than cheque payment to fund the application. The geographic distribution of investors is concentrated in states with major economic activity, in particular Gujarat, Maharashtra, Rajasthan, and Delhi.

The table shows that 78% of treatment and control investors had an account value greater than zero in the month prior to the IPO. Portfolio value amounts are highly skewed so we transform this variable using the inverse hyperbolic sine function[28] – we find that portfolio values, which are on average US$ 530 including zero values, are not significantly different across treatment and control accounts. The next rows show the fractions of treatment and

[27]In the case of IPOs for which our data provider was the registrar, we can directly measure whether or not an account *applied* to an IPO in each of periods +1 to +6. For IPOs where our data provider was not the registrar, we can observe whether the account was *allotted* shares since we see allotments for the entire universe of IPOs from the CDSL data. We set the outcome variable to one in either case – if we see an application for IPOs for which our data provider was the registrar, or if we see an allotment for IPOs not covered by our registrar – and zero otherwise. For the set of IPOs for which we can observe allotments but not applications, our measure is noisy, because although an account had to apply to receive shares, there are also accounts which applied but did not receive shares. We focus on this combined measure because it includes all of the information available to us.

[28]$\sinh^{-1}(z) = \log(z + (z^2 + 1)^{1/2})$. This is a common alternative to the log transformation which has the additional benefit of being defined for the whole real line. The transformation is close to being logarithmic for high values of the $z$ and close to linear for values of $z$ close to zero. See, for example, Burbidge et al. (1988) and Browning et al. (1994).

control accounts that fall into the range of portfolio values described in the row headers. The distribution of portfolio values is roughly U-shaped in both treatment and control accounts, with a relatively large number of accounts with zero value (some of these correspond to new market entrants, or "rookies" as we identify below), and roughly a quarter of the accounts with portfolio values over US$ 5,000.

The next set of variables describes the trading behavior of our treatment and control samples. Gross transactions value (calculated as the sum of the value of stocks bought and sold in a month) is roughly US$ 203 on average including zeros. It is striking that nearly half of the accounts observed traded more than US$ 1,000 in the month prior to treatment. Turning next to the total number of buy and sell transactions undertaken in a month, we find that approximately 31% of accounts made no trades in the month prior to the IPO, and this distribution is also U-shaped. Half of the accounts make between 1 and 10 trades a month. Overall, it appears that the investors in the sample trade substantial amounts, measured either way.

In terms of number of securities in each portfolio, both treatment and control accounts on average hold 9 securities in their portfolio before treatment. In terms of account age at the time of the treatment IPO, approximately 30% of accounts are less than six months old, 33% are between 7 and 25 months old, and 37% are over 25 months old.

Overall, we find that the differences across treatment and control groups are small and typically not statistically significant at standard levels. The fraction of experiments with greater than ten percent significance is around ten percent. Given the similarity of treatment and control groups across this wide set of background characteristics, we confirm that the IPO shares allocated through the lottery mechanism appear to be randomly assigned to investors.

**Main Results.** Table 4 presents our main estimates. The first column presents statistics as of the end of the first day of trading (Listing Day). The remaining columns show the portfolio behavior observed at the end of each event month following the IPO listing (month zero is the listing month). Each row employs a different measure of the holdings of the IPO stock. Within each row header, the first and second rows present the estimated mean of the variable in the treatment and control group from equation 2 respectively and the third row presents the estimated $\hat{\rho}$ from equation 1, i.e., the weighted difference between treatment and control group experimental means.

The first row considers an indicator for whether the account holds any of the IPO stock as the dependent variable. At the end of the first day of trading, we find that approximately 70 percent of lottery winners hold the IPO stock, while only .007 percent of losers hold the IPO stock. The difference is significant at the 1 percent level. One way to interpret this result is that approximately 30 percent of applicants, on average, do not show an endowment effect because their behavior (i.e., not holding the stock at the end of the first day) is consistent regardless of whether they randomly won or lost the lottery. In contrast, 69.3 percent of applicants demonstrate an endowment effect at the end of the first day.[29]

At the end of the listing month (0), lottery winners are 62 percent more likely to hold the IPO stock than lottery losers. This treatment effect declines to 46 percent at the end of six months, with all differences significant at the 1 percent level. The loser group means show that it is relatively rare for lottery losers to own the stock – on average 1 percent of lottery losers own the IPO stock in the month in which it lists, this number only rises to 1.6 percent six months post-listing.

The second row header defines the dependent variable as the fraction of the potential IPO allotment that the account holds. For example, if winners in a particular share category lottery won ten shares and a given account holds five shares, the dependent variable would be defined as 0.5. For lottery losers this variable is also defined as the number of shares of the IPO stock they hold divided by the allotment they *would* have received had they won the lottery. For example if winners won ten shares, then a loser account that chose to

[29]We only present the first day results for the indicator for holding the IPO stock (I(Holds IPO Stock)) because this variable is the most reliably estimated given our data (we only observe monthly holdings data, so we have to make some assumptions to determine whether an account held the IPO stock at the end of the listing day). Appendix A.6 provides details on variable construction.

purchase five shares on the market would have this measure equal to 0.5. For this measure, the treatment effect is slightly smaller at the end of month 1, but otherwise very similar to the first row. However, a comparison of lottery loser means across the first and second variables reveals that conditional on holding the IPO stock, lottery losers choose to hold a substantially larger fraction than the lottery allotment. In particular, Column (1) for month 0 shows that one percent of the lottery losers hold the stock, but their average fraction of allotment is 4.4 percent, implying that lottery losers who choose to own the stock purchase roughly four and a half times the amount of lottery allotment.[30]

The third row is an indicator for whether the account holds exactly the number of shares allotted to winners in the relevant share category. Results here are similar to those in the first row, suggesting that most of the divergence between winners and losers arises from lottery winners continuing to hold initial allotments, while losers are unlikely to purchase the exact allotment they did not receive in the lottery.

The fourth shows the US$ value of the IPO stock held in the portfolio at the end of the month. Lottery winners hold US$ 108 more of the stock than losers on average at the end of the first month, US$ 84 more at the end of the second month, and US$ 55 more at the end of the sixth month. This measure includes differences in chosen holdings between winners and losers as well as returns earned on those shares, meaning that some of the decline in this measure is attributable to significant negative returns on these IPO stocks on average, as we describe below. The fifth row shows the weight of IPO stock in the investor's portfolio, and shows that lottery winners hold 13 percent more of their portfolio in the IPO stock in month 0, which remains substantially higher at 6 percent six months after allotment.

The final rows of the table show average percentage returns to holding the IPO stock to the end of each month. On average the listing return (i.e., the percentage return lottery winners gain over the issue price as soon as the stock begins trading) is 42 percent. The next

[30]Suppose there are 10,000 lottery losers, the lottery allotment (to winners) was 10 shares, and 100 losers purchase the stock (1 percent). Also suppose that those 100 losers choose to purchase 50 shares. Then, the average fraction of the allotment held by lottery losers will be 5 percent (.01*5+.99*0 = .05).

two rows show cumulative returns from holding the stock assuming that the stock was (1) won in the lottery, or (2) purchased at the first trading price. The weights used to calculate these average returns are the same as those in equation 2, i.e., these return estimates combine information across experiments in the same way as in the estimated treatment effects.

The returns data show that lottery winners on average lost money based on their choice to continue to hold the stock after it was initially listed, since returns relative to the first trading price are large and negative. In this sense, lottery losers in our sample make a relatively good decision (on average) to not purchase these IPO stocks at the first trading price. Clearly, what constitutes a good decision depends on the realization of returns in any particular sample, but the key result is that the two groups chose to make substantially *different* decisions about holding the stock.[31]

Table 5 extends the analysis to 24 months after the lottery.[32] We find that even 24 months after allotment, lottery winners are 36 percent more likely to hold the IPO stock than the lottery losers. However, lottery losers' propensity to hold the stock stays relatively constant, at around 1.5 to 1.7 percent over these 24 months.

**The Relationship Between the Endowment Effect and Experience.** We document how the differential holding patterns of the IPO stock vary with plausible proxies of investors' experience in the IPO market. To do so, we interact our main treatment variable in equation 1 with a set of predetermined variables that we believe are interesting proxies for the amount of experience in the IPO market, in a descriptive, non-causal analysis, similar to the analysis in List (2003). Table 6 presents the results.

Column (1) in Table 6 takes equation (1), and adds a set of interactions between the treat-

[31] For example, if this pattern of negative post-issue returns is predictable, then we would expect *both* lottery winners and losers to choose not to hold the stock after listing; it would not be very difficult for lottery winners to have a decision rule where they always sell the stock after it lists, and a simple decision rule like this would eliminate the divergence in behavior. Instead, however, we see a strong divergence in behavior across the groups.

[32] The results for periods one and four months after IPO listing are slightly different from those in Table 4 because we restrict this analysis to those IPOs where we can observe the portfolios of lottery winners and losers at least 24 months after the IPO allotment (i.e. given our portfolio holdings data ends in March 2012 we only include IPOs that occurred in or before March 2010 here). The results for this sample are similar to the results for the full sample in Table 4 in month 1, and the trend is similar through month 8.

ment dummy and various continuous proxies of investors' experience, listed in the rows.[33] Column (2) adds portfolio size and age of the investor account as additional controls to Column (1). Columns (3) and (4) replace these linear interactions with interactions with dummy variables based on tercile or quartile breakpoints of the respective variables. Our discussion below mainly focuses on Column (4).[34]

The first set of rows shows that the estimated endowment effect is highly correlated with the number of IPOs that the winner had been allotted in the past. Accounts which received over 8 (random and nonrandom) allotments in the past have estimated endowment effects that are 17 percentage points smaller than investors with no past IPO experience. However, relative to the base rate listed in the very first row (77.9 percent), even such "experienced" IPO allottees are 60 percent more likely to hold the IPO stock at the end of the first month.

Similarly, the next set of rows show that experience measured by trading activity also reduces the observed endowment effect. Winners with more than 6 trades in the month before IPO allotment are 14.3 percent less likely to hold the IPO stock compared to those with no past trades. Moreover, high numbers of trades are also associated with greater buying activity by lottery losers.

Finally, we measure past return experience by constructing the fraction of *realized* returns in the preceding six months to the IPO allotment that is greater than the listing return observed in the treatment IPO. We find that if the IPO returns are substantially greater than most previously experienced returns, the endowment effect reduces considerably. Interestingly, the reverse seems to be true for the control group – they appear to have a higher propensity to hold IPOs which have higher listing returns than most they have ever experienced, and vice versa.

Figure 1 (c) suggests that some version of the disposition effect may be in operation

[33]We define all independent variables in this regression in the month prior to the lottery allotment to avoid mechanical correlations between the dependent and independent variables due to the lottery allotment.

[34]Note that the reason that the addition of the portfolio and age controls in Columns (2) and (4) changes the winner treatment effect is because this specification includes winner interactions with a set of pre-existing variable.

for lottery winners, and this finding on the role of the past return experiences of lottery winners and losers in explaining their propensity to hold or buy suggests a link between the observed disposition effect and personal experience. These results are also consistent with our previous evidence that wealth effects are unlikely to be driving the endowment effects in our setting (we would expect the effects to get smaller as these returns increase if wealth effects were driving the result).

Overall, these results suggest that there is a correlation between measures of investor experience and smaller endowment effects, consistent with the findings in List (2003). However, having experienced many allotments in the past does not appear to lead to quick and complete elimination of the endowment anomaly in this setting.

The above analysis focused on testing whether the divergence between lottery winners and losers varies based on the total number of IPO lotteries experienced. The advantage of that approach is we have several holistic measure of an investors' total experience in the market. However, it is also possible to estimate the shorter run relationship between experience and endowment effects by testing whether winners in a recent lottery show lower endowment effects in a current lottery. We leave the details of this analysis to the Appendix Section A.4, but note here that while the effects of winning on future endowments is indeed negative, the effect size is small, suggesting that it would take significant numbers of such experiences to reduce the observed endowment effect.[35]

**The Relationship Between the Endowment Effect and Listing Returns.** Figure 1 presents the fraction of the IPO allotment that lottery winners and losers choose to hold of the IPO stock at different time intervals, plotted against the returns accruing on the IPO

[35] It is important to note that there are two potential mechanisms underlying these negative estimates. The first is that winning shares in an IPO causes a given account to exhibit the endowment effect less in a future IPO (i.e. a causal effect of experience). The second is that the types of players who choose to apply to the second IPO after winning shares in the first are differentially selected to be the type who have lower endowment effects (i.e. a selection effect). Previous studies, such as List (2011), focus on separating these two effects, but this is difficult in our setting as the choice to apply for a future IPO is endogenous. However, in this particular analysis the joint effect is a primary object of interest; it tells us whether the two forces of investors learning from experience as well as the force of experiences driving some investors out of the market, lead to lower market anomalies (such as the endowment effect) over time.

stock over that interval. These relationships are particularly useful in testing the theories discussed in the next section.

Figures 1a and 1b plot the fraction of the allotment of the IPO stock held at the end of the listing day on the y-axis. Figure 1a plots this measure against the percentage listing return on the x-axis, while Figure 1b uses instead the dollar value of the listing gain on the x-axis.

Figures 1c and 1d plot the fraction of the allotment of the IPO stock held at the end of the first month post-listing on the y-axis. Figure 1c has on the x-axis the percentage return on the stock to the end of the first month, and Figure 1d replaces this with the change in the dollar value of the IPO allotment over the same interval on the x-axis.

Figures 1a and 1b show that the endowment effect (the average difference between the winners and losers fraction of allotment held) has little relationship with the listing gain. Figures 1c and 1d show that the size of the endowment effect falls sharply with the experienced return on the stock in the month after listing, reminiscent of the disposition effect. We later discuss these results as they relate to the predictions of the theoretical models that we consider.

**Effect Size Comparison.** Appendix Table A.7.3 compares the endowment effect sizes we estimate to those found in recent field studies. Each experiment we report here randomly assigned a good $a$ and good $b$ to participants and then gave them the opportunity to trade for the other good. We define the endowment effect for each study to be the fraction of those endowed with good $a$ who choose to keep it minus the fraction of those endowed with $b$ who choose to trade for $a$.

We find that our low experience sample (defined as either having zero, 1, or 2 previous IPO allotments) has similar endowment effect sizes as the range of effects found amongst the low experience samples in List (2003) and List (2011), despite the very different context (Panel A). Turning to our sample of highly experienced investors, however, we find endowment effects substantially larger than those found amongst the high experience samples in previous field experiments. While it is of course difficult to pinpoint why our effects are larger even for the most experienced subjects, our finding does raise the possibility that experience does not eliminate the endowment anomaly in important field settings.

Overall, our analysis of the relationship between experiences and estimated endowment effects suggests that 1) investors with greater experience exhibit lower endowment effects (due to either a causal effect of experience or selection), and 2) that it is unlikely that experience quickly and absolutely eliminates the endowment anomaly.

Next, we turn to evaluating explanations for our results. We begin by considering a series of explanations that assume that individuals have preferences and beliefs within the standard expected utility maximization framework, but some other feature of the setting causes those endowed to prefer greater holdings of the asset. We then turn to evaluating a set of models which involve non-standard preference specifications or non-standard belief formation. While we describe the intuition behind various models below, we leave the solutions of these models and a more formal presentation to Appendix Section B.

# 4 Standard Expected Utility Explanations

**Transactions Costs, Wealth Effects, and Taxes.** We consider the extent to which wealth effects, monetary transactions costs such as brokerage commissions, disincentives for flipping (i.e., investors might believe they will be penalized in future IPOs if they flip the stock), and tax motivated behavior are possible explanations for our estimated endowment effects.[36] Overall, we find little evidence to suggest these play an important role. We provide the results of specific tests of each of these additional explanations in Appendix A.5.

**Simple Substitution Effects.** One possibility is that investors who lose the IPO lottery decide to buy a substitute stock (i.e., a stock to take the place of the IPO stock that they lost in the lottery, which they were unable to secure at the issue price). This behavior could

[36] Our discussion of wealth effects also includes the possibility of a "house money effect" explaining our results, as both are unlikely to explain our results for similar reasons. See appendix for details.

potentially generate an endowment effect; lottery winners would tend to hold the IPO stock because winning that IPO satisfied their demand, and lottery losers would own a different stock (with potentially similar characteristics). If this were a common phenomenon it would reduce the economic magnitude of the endowment effect broadly construed, as if we defined the losers' comparison holdings more broadly (for example as any stock in the same industry as the IPO stock) we might find small differences across lottery winners and losers.

Contrary to this hypothesis, however, we find that at the end of the month after the IPO stock lists the lottery winners hold almost exactly one additional stock relative to the lottery losers. This means that lottery losers are not buying different stocks to close the gap in the number stocks of held (Appendix Figure E.4). Moving forward in time in Appendix Figure E.4, we also see that the trends in the lottery winner and loser groups are almost exactly parallel, once again suggesting that the lottery losers do not make differential purchases in substitute shares. Finally, in Anagol et al. (2015) we find that lottery winners are actually 5 to 7 percentage points more likely to buy non-IPO stocks than lottery losers. If lottery losers were substituting their lottery loss with other shares, we should observe lottery losers being more likely to buy non-IPO stocks in the future. Taken together, these results suggest that lottery losers are staying out of the IPO stock as well as staying out of other shares, and that lottery winners are holding substantially more shares as a result of the randomized endowment.

**Inertia at the Portfolio Level.** While many economic models assume that investors constantly monitor and adapt their portfolios to changes in information and returns, substantial evidence exists that in practice investors are much slower to respond, and instead are better characterized as being inertial or following the "path of least resistance" (Baker et al., 2007; Mitchell et al., 2006; Madrian and Shea, 2001). Given that our main results (that lottery winners tend to hold the stock while losers do not) comes from inaction on the part of investors in the IPO stock, inertia is naturally a good description of their behavior. In this section we are interested in evaluating whether this inertial behavior is specific to the

IPO stock, or whether it is driven by inertial behavior at the portfolio level as a whole. If our results are due to the fact that investors are not making any transactions in their entire portfolios, then this obviously would reduce the relevance of our study to other settings where endowment effects may be present. However, if the inertial behavior is specific to the IPO stock, it is interesting to evaluate different theoretical models that could generate the endowment effects observed in the IPO stock (which we turn to in the next Section).

Perhaps the most natural way to conceive of inertia at the portfolio level is that there are substantial costs to making transactions, leading to investors optimally choosing to remain inactive. Such costs would naturally generate an endowment effect, since lottery winners and losers remain at the status quo (winners hold, and losers never buy) as neither group alters their portfolios in the future. Examples of such costs (other than standard monetary transactions costs and taxes, discussed above) might include include "irritation costs" (e.g. lost passwords or account numbers), as well as procrastination arising from a high opportunity cost of time.

A key prediction if such costs are responsible for our results is that the observed endowment effect should be much smaller for accounts that we observe making trades in other stocks aside from the IPO stock in question. If an investor makes a buy or sell trade in another stock, it seems difficult to argue that they could not overcome the forces preventing a trade on the IPO stock, as the marginal cost of putting in a trade on the IPO stock in addition to trades on other stocks is low. Appendix Table A.7.2 shows estimated endowment effects for lottery winners and losers conditional on the number of trades made in non-IPO stocks, and finds a substantial endowment effect even for investors who made more than 20 trades in non-IPO stocks in the same month.

An additional, related, possibility is that winners do not trade the IPO allocation because it might be smaller than the investor's other positions, i.e., the investor may find it worthwhile to pay costs to trade in stocks where he or she has a larger position, but not those in which they have relatively smaller positions. We test this variant by estimating the endowment effect for accounts that, in the month prior to winning or losing an IPO allotment, had an average value of buy or sell transactions that was less than the value of the allotment, or make trades in a position size that is less than or equal to the IPO allotment value.

For example, suppose IPO A allotted lottery winners 150 dollars worth of shares. In this case, we check the prevalence of the endowment effect in each month for investors in IPO A that had an average value of purchases less than 150 dollars and made at least one purchase, an average value of sales less than 150 dollars and made at least one sale, or met both these criteria.[37] We also check the prevalence of the endowment effect for investors who made any transactions in other stocks in their portfolios worth less than or equal to 150 dollars.

Table 7 presents the results. We find that lottery winners in this sub-sample are 58 percent (or 51 percent for the position-size measure) more likely to hold the IPO allocation at the end of the allotment month relative to lottery losers, significant at the 1 percent level. This result is approximately four percentage points (and statistically different from), our result in the full sample of 62.4 percent, which is consistent with the idea that investors who make these small trades have a slightly smaller endowment effect. However, these results are not consistent with the idea that our full sample results are mainly due to most investors ignoring these small transactions, as we find very large endowment effects for even those investors who have recently made a "small" transaction. These accounts also show large endowment effects as we move through time after the allotment. Overall, these results do not appear to support a model where substantial costs of initiating a transaction, combined with the small value of the IPO allotment, are the main drivers of the effects.

Finally, in related work we find that lottery winners are more likely to trade non-IPO stocks in their portfolio than lottery losers, suggesting that, if anything, winning the lottery reduces the transactions costs associated with making a trade (Anagol et al., 2015). This result also goes against the idea that portfolio-level inertia is responsible for our results.

Taken together, the results above suggest that our finding of endowment effects in this

[37] We need to require that the account had least one purchase, otherwise an account with no activity would be defined as an account that made a "small trade".

setting are driven by a very specific type of inertia that holds in the IPO stock, but not in the whole portfolio. In the next Section, we present and empirically test economic models that can generate inertia specifically in the IPO stock in our setting.

**Information Acquisition Costs and Incentives.** Van Nieuwerburgh and Veldkamp (2010) present a model where investors' decisions to learn about assets are jointly determined with their choices to hold those assets. In particular, the mechanism in their model is that investors choose to invest in information about securities they *expect* to hold; once they have acquired information about the stock it becomes optimal to hold more of the stock, and then once they hold more of the stock it is optimal to invest more in learning about it (because a given information signal is more valuable if the investor owns more shares).

In our setting, both lottery winners and losers should have the same expectations of holding the stock before the randomized allotment is made, so their incentives to learn about the stock should be the same before the allotment is made. Therefore, at the time of allotment, winners and losers should be balanced in the amount of information they have about the IPO stock. However, once winners are endowed with the stock, the model predicts that their incentive to acquire additional information about the IPO stock should be higher, which might be an explanation for the divergence that we observe.[38] On the other hand, one important feature of our results runs contrary to this explanation for our observed endowment effect. Lottery winners continue to hold the IPO stock even though it produces negative 33 percent returns on average, 6 months after issuance, and negative 62 percent, 24 months after issuance. In other words, if lottery winners are acquiring more information about the IPO stock, they appear to be acquiring particularly poor quality information that is causing them to hold an underperforming asset.

**Multiple Applications Per Household.** As discussed earlier, households may have an incentive to submit multiple applications through different brokerage accounts to increase

[38]Note that for this explanation to apply, it must be the case that there are some transactions costs associated with purchasing the IPO stock; if there are no transactions costs then the lottery losers could costlessly acquire the IPO stock and therefore have roughly the same incentives (modulo the listing gain, which they cannot access) to acquire information about it.

their probability of winning. Could this behavior explain the endowment effect? First, it is not obvious that submitting multiple applications is a good strategy as only approximately one-third of IPOs end up being over-subscribed enough to warrant lotteries. By submitting multiple applications with the intention of only holding the ones that are allocated households would take on the substantial risk of all of their accounts getting allotted. Note also that this behavior would have to be common in almost every IPO share category in our dataset, as the endowment on the listing day is large in almost all share categories (See Figure 1a and 1b), and since some of these share categories had quite large probabilities of allotment (see Table 2). Nevertheless, we explore this further in the appendix, and find other features of this explanation appear strongly inconsistent with our results.[39]

# 5 Non-Standard Explanations

In this Section we consider a series of theoretical models that have either been prominent explanations of endowment effects or of investor behavior related to our results (such as the disposition effect) in past work. We aim to determine 1) to what extent these models can generate an endowment effect when set up and solved in environments approximating our real-world setting, and 2) derive additional testable predictions to see whether they hold up in the data. Our goal here is not to conclusively determine which model explains all of our empirical facts, but instead to provide guidance for future empirical work that tests theoretical mechanisms that might drive endowment effects in the field.

**1. Expectations Based Reference Dependent Loss Averse Preferences.** While a number of potential causes of endowment effects have been studied, the most prominent is based on the idea of reference dependent preferences with loss aversion first proposed in Kahneman and Tversky (1979). A key challenge for this model is the determination of the appropriate psychological reference point around which agents are loss averse. As

[39]For example, because the randomization is orthogonal to households' application behavior, this explanation would predict there should be a large amount of buying amongst households where all of the accounts were not allocated – we do not observe this in the data.

different reference points yield different predictions in this (and other) settings, we analyze the implications of a number of different theoretical formulations of the reference point.

***Expectations as Reference Points – Constant Prices***: Kőszegi and Rabin (2006) present a theory where recently formed expectations about future outcomes determine an agent's reference points. In the case of exchange experiments (i.e., those in which subjects are randomly endowed with good A or B, and then asked if they would like to trade), one simple prediction is that subjects might *expect* to be forced to leave with the good with which they were just endowed, and so ownership of the good is the relevant recently-formed reference point. Relative to this reference point, the option of trading the good away is encoded as a loss, and subjects thus tend to hold endowed objects more than would be predicted by standard expected utility preferences.

Ericson and Fuster (2011) set up and solve a model which provides them with theoretical guidance for a laboratory experiment which considers endowments of mugs and pens. We essentially relabel the mug and pen in their model as the IPO stock and cash, and present the conditions necessary to predict an endowment effect in this model (see appendix for details). To do so, we assume that the price of the stock does not vary post-listing, and apply the model formulating the reference point as agents' either expecting to own the stock, or expecting to hold cash equivalent to the stock price (depending on agents' individual preferences for cash vs stock).[40]

The key parameter in this model is $b$, the probability the agent assumes they will be allowed to trade the endowed stock for cash. In laboratory settings, $b$ can be experimentally varied, but in field settings, agents will have their own expectations about whether the economic environment will permit trading of the endowed object. An important testable prediction of this model is that the extent to which the endowment shapes the reference point depends on subjects' expectations of $b$ (Ericson and Fuster, 2014). The model shows that the predicted endowment effect gets weaker as the probability that agents expect to be

[40] Note this assumes that investors narrowly frame their decisions about the IPO stock, i.e., they do not combine potential outcomes with the other risky assets that they hold.

able to trade ($b$) increases; in the limit, when $b = 1$, there is no endowment effect.

In our stock market setting, we argue that investors likely believe $b = 1$ (or at least, that $b$ is very close to 1) given that stocks are traded on the exchange daily. If so, this model cannot explain our findings. Our results are therefore interesting in light of three recent laboratory studies Ericson and Fuster (2011); Heffetz and List (2014); Goette et al. (2014) that have experimentally varied $b$, and find conflicting evidence on whether endowment effects are eliminated when subjects fully expect to be able to trade in the future (i.e., $b = 1$). Our results suggest, at a minimum, that endowment effects are possible in markets outside the lab even when agents fully expect to have the opportunity to trade the endowed objects in the future.

***Expectations as Reference Points – Expected Distribution of Prices.*** Within the Kőszegi and Rabin (2006) framework, an alternative potential reference point agents might have is ownership of the stock evaluated using the *expected distribution of future prices* of the IPO stock, rather than a constant future price. Interestingly, the expectations based reference point theory of Kőszegi and Rabin (2006) predicts that decision makers will be less risk averse when the reference point is stochastic and face the choice of a constant alternative (i.e., IPO lottery winners under this more sophisticated formulation), and more risk averse when the reference point is fixed and they face the choice of a stochastic alternative (i.e., IPO lottery losers – assuming that they consider their reference point as holding cash). The fact that lottery winners take greater risk by continuing to hold the IPO stock, while lottery losers choose not to purchase the IPO stock appears consistent with this prediction of the model, under this formulation of reference points.[41]

In the appendix we present a model where lottery participants have expectations based stochastic reference points. In the model, reference points are determined by expectations, which in turn are determined by the lottery participant's plan of action (which is chosen

[41]Sprenger (2015) and Song (2015) both present laboratory evidence confirming this prediction of the KR theory. Note that neither standard expected utility theory nor disappointment aversion (another leading theory of reference point determination where the reference point is based on the certainty equivalent of a gamble), predict this so called "endowment effect for risk."

prior to the stock listing). Lottery losers consider two possible plans; one where they do not buy the IPO stock after it lists, and one where they do buy the stock. Similarly, lottery winners consider a plan to sell the stock versus a plan to hold the stock. We are particularly interested in deriving the conditions necessary for an endowment effect to appear: the same agent should want to stick to the plan of holding the stock if they win the lottery, but simultaneously want to stick to the plan of not holding the stock if they lose the lottery.

We find that the model can generate an endowment effect, in the sense that there is a range of probabilities regarding the future success of the stock for which the "endowment effect plan" to hold stock if the agent wins and not buy the stock if the agent loses the lottery is a "personal equilibrium" (PE) in the language of Kőszegi and Rabin (2006). The main intuition for this result is the same as in Sprenger (2015), i.e., that agents demonstrate an "endowment effect for risk" – they exhibit lower risk aversion when endowed with a gamble and consider trading it for cash, than when they are endowed with cash and consider trading it for a gamble. The range of probabilities of $q$ that can deliver this effect, however, are limited – in an example calculation from our model in the appendix (assuming the stock can go up or down a fixed amount with probability $q$), the agent will demonstrate an endowment effect if $0.4 < q < 0.6$. In particular, the probability of the up state has to be high enough so that the agent sticks to holding the stock when they win, but simultaneously has to be low enough so that the agent also sticks to the cash if they lose the lottery.

The PE condition satisfied by these parameter values only guarantees that the agent does not wish to deviate from the endowment effect plan. However, it does not guarantee that pursuing this plan delivers the agent the highest expected utility of all possible plans. When we derive these conditions (for a "preferred personal equilibrium" or PPE Kőszegi and Rabin (2006)), we find that there is no value of $q$ that can make the the endowment effect plan a PPE. The intuition for the result is that planning to buy the stock and then following through on it (as a lottery loser) delivers exactly the same payoff as planning to hold the stock and following through on it (as a lottery winner). Similarly, planning not to buy the stock and following through on it as a lottery loser gives the same payoffs as planning to sell the stock and following through on this plan as a lottery winner. Given this symmetry of payoffs, the model cannot generate losers who get higher expected utility from staying out while simultaneously getting winners to get higher expected utility from staying in the stock.

Thus, while it is possible that this model can generate the endowment effect, it would require us to assume that investors are consistently not choosing their highest expected utility plans. Given this we believe that it is unlikely that this framework is the sole explanation for the endowment effect in our context.

***Expectations as Reference Points – Model Including Lottery and the IPO After Market.*** The reference dependent models presented so far abstract away from the fact that the random assignment in our empirical setting occurs in lotteries with different probabilities of winning, and in IPOs with different listing gains. In Appendix B, we present a model of an agent with expectations based reference dependent preferences who has chosen to enter the lottery for an IPO stock, experiences a listing gain, and decides on a plan of action based on whether or not she wins the lottery, as well as on how the stock performs in the aftermarket. This model is a more realistic characterization of our empirical setting.[42]

In the model, an agent enters an IPO lottery, and wins (loses) with probability $p$ $(1-p)$ and receives (does not receive) the stock. After the agent learns whether or not she won the stock, the stock lists on the exchange at a price greater than the price paid for the stock (i.e., there is a listing gain). Following realization of the listing gain, the investor chooses whether to hold or sell the stock if she wins the lottery, and whether or not to purchase the stock if she loses the lottery. Finally, after this choice is made, the stock either goes up with probability $q$, or down with probability $1-q$.

We analyze the model exactly as suggested by Kőszegi and Rabin (2006). Before the lottery results are announced, the agent considers three possible plans of action. The first,

[42]We refer the reader to Appendix B for the details of the model, but focus on presenting the basic setup and the intuition for our results in the paper.

we which term the "never hold" plan, is to sell the stock immediately if she wins, and not buy the stock if she loses. The second plan ("always hold"), is to hold the stock if she wins and buy if she loses the lottery. If the agent follows through on either of these first two plans then there is no endowment effect, because the agent has the same position in the stock at the end of the model *regardless* of whether they were randomly assigned the stock in the lottery. The third "endowment effect" plan is to hold the stock if she wins, but not purchase the stock if she loses the lottery.[43]

In the model, the agent's decisions affect her utility in two ways. First, her choices affect her consumption directly (i.e., by the amount of the value of the stock or cash held at the end of the model). Second, the agent feels gain-loss utility when comparing her actual outcome to her expectations-based reference point. For example, she might experience a utility gain from comparing an outcome of winning the lottery and holding a stock which goes up to losing the lottery and buying a stock which goes down.

Our goal in analyzing the model is to determine the conditions under which the agent does not deviate from the endowment effect plan to either the always hold plan or the never hold plan.[44] When we solve the model, we find that the expectations based reference dependent framework can generate an endowment effect in this setting. It is worth considering the forces in the model that makes an agent choose the endowment effect plan. The first force is the direct consumption benefit arising from the stock's after-listing performance. These direct consumption benefits alone will never move an agent towards the endowment effect plan – if she expects the stock will do well in the aftermarket, this moves her towards the always hold plan, and if she expects the stock to do poorly, this moves her towards the never hold plan. This means that the reference-dependent gain-loss utility piece (which is the non-standard part of this utility formulation) is what pushes the agent towards the

[43] There is a fourth possible plan, where the agent chooses to sell the stock if she wins the lottery but purchase the stock if she loses the lottery. Given that this plan is not empirically relevant, we omit it from our discussion here.

[44] This is the condition necessary to guarantee that sticking to the endowment effect plan is a personal equilibrium (PE).

endowment effect plan.

While we leave the details of the full derivation to the Appendix, we focus here on one derived condition that is easily tested in our data. The condition shows that as the probability that the agent wins the lottery ($p$) goes to one, that the endowment effect can only be generated for a stock with an expected return very close to zero. The intuition for this result is that the endowment effect in this model is driven by the agent comparing how she feels when she wins the lottery to how she feels when she loses; however, as $p$ goes to one this comparison becomes less and less important because the agent's reference points are less and less affected by her expectations of losing the lottery (since $1 - p$ goes to zero). When $p$ is close to one the agent's decisions are essentially determined by the expected return on the stock. If this is positive she will prefer the always hold plan, and if negative, she prefers the never hold plan.

Looking at our empirical estimates of how the endowment effect varies with the probability of winning a given lottery (Table 5), we find that when $p$ goes from zero to one, the endowment effect only goes down from 0.78 to 0.74. It is true that that the estimated endowment effect gets smaller as the probability of winning is consistent with this model, but it seems implausible that 74 percent of lottery applicants believe that the return on the IPO stock is in a very narrow range around zero. For example, such beliefs are very different from the observed empirical distribution of IPO returns over our sample period – only 1.8 percent of our sample IPOs had returns between zero and one percent over six months.

To summarize, while this model can generate endowment effects, the data do not support the important prediction that the endowment effect should be strongly influenced by the agent's expected probability of winning the lottery.

**2. Issue Price as a Reference Price (Weaver-Frederick Model).** Another candidate explanation for endowment effects in general (including those in our setting) is that lottery losers have an "aversion to bad deals" as described in Weaver and Frederick (2012); in particular, lottery losers might see purchasing the stock after the IPO as a "bad" deal because the stock typically trades higher than the issue price (even though the issue price is irrelevant for the future performance of the stock). We formally apply the model of Weaver and Frederick (2012) to our setting in the appendix, but simply summarize the main results of the model here.

The model can generate an endowment effect because lottery losers' valuations of the stock are distorted downwards due to their disutility from having to pay a price higher than the issue price. However, this distortion does not occur for lottery winners because they already own the stock, and therefore do not have to transact at the listing price to add it to their portfolio.

In addition to predicting an endowment effect, the model also predicts that the endowment effect should get smaller as the listing gain gets smaller. The intuition for this result is that as the listing gain gets smaller, lottery losers have the opportunity to buy the stock at a price closer and closer to the price that lottery winners paid. The motivation for lottery losers to feel like they are getting a "bad deal" when they purchase the stock in the aftermarket therefore declines as the listing gain decreases.

Contrary to this prediction, however, we find in Figure 1 Panels (a) and (b) that there is little evidence of a relationship between the size of the listing gain and the endowment effect. While we cannot be sure to what extent this model helps explain the endowment effect when the listing gain is large, the fact that the effect is so strong for small listing gains suggests that this model is insufficient on its own as an explanation of our results.

**3. Realization Utility Model with Loss Aversion**: In the appendix, we present a model where the investor gets utility from realized gains and losses relative to the purchase price, i.e., utility from trading in the stock market comes not from future consumption or wealth levels, but instead in the instant the stock is sold. We are motivated to apply this model to our setting because realization utility with loss aversion is the leading theoretical explanation of the disposition effect (Shefrin and Statman (1985) , and Barberis (2013)), and we clearly observe disposition-effect type behavior amongst lottery winners in how they trade the IPO stock in the aftermarket – winners are more likely to sell IPO stocks that have gained versus lost value as can be seen in Figure 1c and 1d.[45] Our primary question of interest is whether a realization utility model with loss aversion can also explain the fact that lottery winners are so much more likely to hold the IPO stock than lottery losers (i.e., the endowment effect).

In this model, lottery winners choose whether to sell or hold the stock after the listing gain is realized. The key feature is that lottery winners' realization utility is based on the comparison of the listing price (the price they can sell at on the first day) with the issue price (i.e., the issue price is the reference point). We find that this model can generate an endowment effect, but it additionally predicts that the endowment effect should go to zero as the listing gain goes to zero (this prediction is shared with the Weaver-Frederick model). Below, we explain the intuition for this result, considering the cases of small and large positive listing gains, and refer the reader to the appendix for analysis of the negative listing gain cases (which are intuitively similar).

First, consider the case where the listing gain is so large that regardless of the stock's future performance, the lottery winner will always be able to sell at a gain relative to the issue price. In this case, the lottery winner will be in the gain domain regardless of whether he sells right after listing, or chooses instead to hold. However, if the lottery loser were to buy the stock at the listing price, there is the chance that the stock will go down, meaning that he will be in the loss domain. Because the loser has the chance to end up in the loss domain (but the winner does not), he must expect a higher post-listing return on the stock to be willing to hold it, meaning that lottery losers will be less likely to hold the stock in general. As a result, the model predicts an endowment effect in this case.

[45] There is an active debate in the literature regarding to what extent the realization utility model can explain the disposition effect as well as other features of the relationship between past returns and individual investor selling behavior. Ben-David and Hirshleifer (2012) consider the extent to which realization utility can explain the relationship between past returns and selling behavior. While the basic empirical pattern of investors who hold the stock selling more as returns increase is similar in our setting to theirs, we also observe the universe of counterfactuals (lottery losers), meaning that the endowment effect also needs to be explained in our setting.

Next, consider the case where the listing gain is small and positive, such that there is a chance that a lottery winner might have to sell at a loss relative to the issue price. The model can also generate an endowment effect in this case, because even though the lottery winner can potentially land in the loss domain, the size of this loss is buffered by the realization utility that comes from the listing gain. However, the lottery loser does not have this listing gain buffer, and thus experiences the full loss if the stock goes down after listing. The model thus generates a wedge between the winner and the loser, and the associated endowment effect, but this effect gets smaller and smaller as the listing gain approaches zero, since the listing gain buffer is also zero at that point.

As discussed for the Weaver-Frederick model, Figure 1 Panels (a) and (b) do not show a pattern of smaller endowment effects for smaller listing gains. Moreover, in our regression analysis in Table 5, we find that the largest endowment effects occur for IPOs with closer to zero gains, and smaller endowment effects are seen in IPOs with either negative or highly positive listing gains. This is an important rejection of this model – the realization utility of agents depends fundamentally on the size of the listing gain, but our empirical results do not reveal a significant relationship between the listing gain and the endowment effect.

Overall, while a realization utility model may be useful to explain lottery winners' tendency to sell winning versus losing IPO stocks in the first month after listing, it does not provide a good explanation for why lottery winners are so much more likely to hold the IPO stock in our setting (i.e., the endowment effect).

**4. Salience Model.** The main idea of the salience model, as first suggested in Bordalo et al. (2012) is that agents have distorted probabilities of different states of the world occurring, and this distortion is based on how "salient" the payoffs in that state are. We consider two variants of salience models. The purpose of the first model is to show that a salience mechanism can plausibly generate the behavior of winners post-listing; given this, we pursue the second variant of the model, in a more realistic setup which includes the initial application lottery, to see if salience can generate the endowment effect that we see.

In the first model (see the Appendix for details), we consider the behavior of the lottery winner after he experiences a high, medium, or low listing gain, and forms distorted beliefs[46] about the future probability of high, medium or low returns based on this listing gain. When the winner experiences a low listing gain, the salient payoff is the possibility of a large rebound in the stock, and therefore the investor will tend to hold the stock. If the stock has a medium listing return, neither a future gain or loss on the stock is salient and the agent uses the objective probabilities to calculate expected values. If the stock has a high listing gain, the salient outcome is a large drop in the future, so this probability gets overweighted, and the investor tends to sell the stock.

This simple model provides a plausible explanation for the pattern of selling we observe amongst lottery winners in Figures 1c and 1d. Given that this framework is able to explain the behavior of lottery participants subsequent to winning, we go on to develop a model of the IPO lottery itself to understand whether a salience mechanism might also explain why lottery winners are so much more likely to hold the stock than lottery winners.

This model of the IPO lottery follows a similar setup to our model of expectations based reference-dependent model discussed above, with two changes. First, the agent only considers the consumption utility resulting from stock price outcomes, not the gain-loss utility pieces.[47] Second, agents in the model have distorted probabilities regarding future outcomes of the stock based on the salience of these payoffs.

The general result is that the states of the world where the agent wins the lottery are less salient, because in those cases the agent always receives the listing gain, and (in the short run, such as the day after listing) this swamps the magnitude by which the stock goes up or down. The cases in which the agent loses the lottery are more salient, because lottery losers get a zero payoff under plans where they do not buy the stock, but a potentially high

[46]We apply the salience based distortion factor defined in Bordalo et al. (2012), which is a function of the distance between the highest and lowest outcome within each state of the world normalized by the total payoffs across all lotteries within that state.

[47]This is to allow us to focus on the "pure" role of the salience distortion as opposed to the role of gain-loss utility.

payoff under plans where they purchase the stock and it goes up. Furthermore, within the categories of winning or losing the lottery, the state where the stock goes down in price is more salient than the one in which the stock goes up in price. This is because the percentage change in the price when the stock goes down (relative to an equivalent gain) is larger relative to the total possible payoffs in that state of the world.

These patterns imply that a salience based thinker will rank states of the world from highest to lowest salience as follows: 1) lose lottery and stock goes down 2) lose lottery and stock goes up 3) win lottery and stock goes down 4) win lottery and stock goes up. This salience ranking will typically make the never hold plan (i.e., sell if win, do not buy if lose) dominate the endowment effect plan (i.e., hold if win, do not buy if lose). We discuss this result in a more nuanced fashion in the appendix, but essentially, for any model based on probability distortions (such as a salience based model) to produce an endowment effect, it would require the agent to specifically overweight the probability that the stock will go up when they win, but downweight this probability when they lose.

Given this result, we argue that a salience based framework, while a potentially plausible explanation of the winner's behavior in the aftermarket, is unlikely to be able to fully explain the endowment effect.

**5. Inattention Model.** A key empirical prediction that most of the models above are unable to explain is why lottery losers are so reluctant to buy the stock, irrespective of the size of the listing gain or probability of winning. One possible hypothesis that addresses this failure is that lottery applicants might only pay attention to the stock upon learning that they have won; once they learn they have lost the IPO lottery, the IPO stock might exit their attention set, meaning that it is almost never purchased. Note that this is not the same as the cost-based explanations considered in our discussion of inertia, since what we refer to here is a specific behavioral mechanism of attention allocation (or the lack thereof).

We do not formally model why lottery losers stop paying attention to the stock after they lose the lottery, but suggest two potential microfoundations for this behavior. One is that investors may employ the heuristic of first paying attention to stocks in their portfolio before allocating limited attention to other possible stocks. A (related) microfoundation is that winning the stock in the lottery provides "exposure" to the stock, which keeps it in the attention set of winners; but since losers do not receive this exposure, it remains out of the attention set for them (see Bordalo et al. (2015)).

In the Appendix, we present a very simple model of inattention. As above, we assume that lottery losers are completely inattentive to the stock, to match our empirical results. We also assume that some fraction of lottery winners are inattentive to the stock, and will therefore hold the stock either if they are not paying attention to it, or if they are paying attention to it but believe that it is worth more than its current market price. According to this simple model, the endowment effect will increase in the number of winners who are inattentive to the stock, controlling for private valuations.

The ideal test of this theory would be exploit variation in the degree to which winners pay attention to the stock, but this is difficult in the absence of direct observations of attention. Previous work has argued that investors pay attention to stocks in their portfolio that have extreme returns (see for example, Barber and Odean (2008) and Hartzmark (2015)), and we find mixed evidence to support this. Winners are more likely to sell very high return IPOs, consistent with the attention hypothesis. However, they are less likely to sell very low return IPOs, suggesting that a simple attention based model is not adequate to explain the longer run behavior of the winners.

**Summary of Theoretical Explanations**

We argue that none of the standard theoretical frameworks studied above can independently provide an adequate description of the endowment effect we find in addition to the other empirical facts that we uncover.

At a minimum, it appears that an important ingredient to explain our results is inattention to the IPO stock on the part of lottery losers – since losers almost never buy the IPO stock, irrespective of the listing gain. However, any such model of inattention has to be combined with another model (such as the realization utility model, the Weaver-Frederick model, or the salience model), to meaningfully explain the behavior of the lottery winners in the aftermarket.

# 6 Conclusion

In the absence of important wealth effects or transactions costs, standard economic theories predict a fundamental symmetry: the same person should not make different decisions about whether to hold an asset depending on whether he or she is endowed with the asset. Data on the behavior of applicants to Indian IPO lotteries refutes this prediction. We find that randomly receiving shares in an IPO increases the probability that an applicant holds these shares for many months after the allotment, and that standard factors such as inertia at the portfolio level, wealth effects, taxes, and transactions costs are unlikely to explain these effects.

We highlight two broad contributions of our work. First, our results suggest that endowment type effects may have important implications for naturally occurring asset markets, in addition to the consumer (mugs, pens) and durable goods (sports cards, collector's pins) markets where they have most commonly been studied. Second, our results lend credence to theoretical frameworks, such as those presented in Thaler (1980), Kőszegi and Rabin (2006), and Bordalo et al. (2012) where an agents' decision process regarding an asset fundamentally changes once the asset enters their portfolio; lottery winners do not have any standard reasons to value the IPO stock more than lottery losers in our setting, but yet continue to hold it at much higher rates. Although our field context does not allow us to definitively determine which variant of these models best explains our evidence, exploring the empirical validity (in other settings) and general equilibrium implications of this type of buyer/seller divergence appears to be a fruitful area for future research.

Table 1: Example IPO Allocation Process: Barak Valley Cement IPO Allocation

| Share Category | Shares Bid For | # Applications | Total Shares | Proportional Allocation | Win Probability | Shares Allocated | # Treatment group | # Control group |
|---|---|---|---|---|---|---|---|---|
| $c$ | $cx$ | $a_c$ | $a_c cx$ | $\frac{cx}{v}$ | $\frac{c}{v}$ | | $\frac{c}{v} \times a_c$ | $(1 - \frac{c}{v}) \times a_c$ |
| (0) | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| 1 | 150 | 14,052 | 2,107,800 | 4 | 0.027 | 57,000 | 380 | 13,672 |
| 2 | 300 | 9,893 | 2,967,900 | 8 | 0.054 | 80,250 | 535 | 9,358 |
| 3 | 450 | 5,096 | 2,293,200 | 12 | 0.081 | 61,950 | 414 | 4,682 |
| 4 | 600 | 4,850 | 2,910,000 | 16 | 0.108 | 78,750 | 525 | 4,325 |
| 5 | 750 | 2,254 | 1,690,500 | 20 | 0.135 | 45,750 | 305 | 1,949 |
| 6 | 900 | 1,871 | 1,663,900 | 24 | 0.162 | 45,450 | 304 | 1,567 |
| 7 | 1050 | 4,806 | 5,046,300 | 28 | 0.189 | 136,500 | 910 | 3,896 |
| 8 | 1200 | 2,900 | 3,480,000 | 32 | 0.216 | 94,050 | 628 | 2,272 |
| 9 | 1350 | 481 | 649,350 | 36 | 0.244 | 17,550 | 117 | 364 |
| 10 | 1500 | 1,302 | 1,953,000 | 41 | 0.271 | 52,800 | 352 | 950 |
| 11 | 1650 | 266 | 436,900 | 45 | 0.298 | 11,850 | 79 | 187 |
| 12 | 1800 | 317 | 570,600 | 49 | 0.325 | 15,450 | 103 | 214 |
| 13 | 1950 | 174 | 339,300 | 53 | 0.352 | 9,150 | 61 | 113 |
| 14 | 2100 | 356 | 747,600 | 57 | 0.379 | 20,250 | 135 | 221 |
| 15 | 2250 | 20,004 | 45,009,000 | 61 | 0.406 | 1,217,700 | 8119 | 11,885 |

Note: Columns (7) and (8) are obtained after applying the regulation defined rounding off methodology as described in section 2.1.

Table 2: Characterizing Lottery Application and Allotment Experience

| Treatment Characteristics | | Percentile Across Experiments | | | | |
|---|---|---|---|---|---|---|
| | Mean | 10 | 20 | 50 | 75 | 90 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Application Amount ($) | 1750.56 | 155.29 | 343.34 | 791.74 | 1397.62 | 2093.73 |
| Probability of Treatment | 0.36 | 0.09 | 0.20 | 0.37 | 0.64 | 0.84 |
| Allotment Value ($) | 150.29 | 125.60 | 130.33 | 142.76 | 158.53 | 169.40 |
| First Day Gain/Loss (%) | 39.18 | -7.57 | 6.10 | 17.13 | 37.08 | 87.77 |
| First Day Gain/Loss ($) | 61.89 | -11.14 | 8.49 | 24.78 | 53.03 | 136.94 |
| Median Portfolio Value (t-2,$) | 1748.47 | 722.74 | 1088.22 | 1594.63 | 2270.57 | 2999.05 |

## Table 3: Randomization Check

| | Treatment Mean (1) | Control Mean (2) | Difference (3) | % Experiments > 10% significance (4) |
|---|---|---|---|---|
| Applied/Allotted an IPO | 0.379 | 0.379 | 0.000 | 8.97 |
| Cutoff Bid | 0.926 | 0.925 | 0.001 | 10.96 |
| Application by Blocked Amount (ASBA) | 0.047 | 0.048 | -0.001 | 4.43 |
| States of India | | | | |
| Gujarat | 0.354 | 0.352 | 0.002* | 12.27 |
| Maharashtra | 0.212 | 0.211 | 0.000 | 10.44 |
| Rajasthan | 0.150 | 0.151 | -0.001 | 8.87 |
| Delhi | 0.045 | 0.045 | 0.000 | 8.61 |
| Portfolio Value > 0 | 0.786 | 0.785 | 0.000 | 11.48 |
| IHS Portfolio Value | 6.673 | 6.667 | 0.006 | 13.05 |
| Portfolio Value = 0 | 0.214 | 0.215 | 0.000 | 10.18 |
| Portfolio Value = 0 to 500$ | 0.129 | 0.129 | 0.000 | 12.94 |
| Portfolio Value = 500 to 1000$ | 0.087 | 0.087 | 0.000 | 10.18 |
| Portfolio Value = 1000 to 5000$ | 0.317 | 0.317 | 0.000 | 8.09 |
| Portfolio Value > 5000$ | 0.252 | 0.252 | 0.000 | 9.39 |
| IHS Gross Transaction Value | 5.342 | 5.350 | -0.008 | 8.61 |
| Transaction Value = 0 | 0.318 | 0.317 | 0.001 | 9.66 |
| Transaction Value = 0 to 500$ | 0.175 | 0.175 | 0.000 | 10.96 |
| Transaction Value = 500 to 1000$ | 0.115 | 0.116 | 0.000 | 9.66 |
| Transaction Value = 1000 to 5000$ | 0.283 | 0.283 | 0.000* | 11.22 |
| Transaction Value > 5000$ | 0.108 | 0.109 | -0.001* | 8.87 |
| Gross No. of Transactions | | | | |
| No. of Transactions = 0 | 0.318 | 0.317 | 0.001 | 9.66 |
| No. of Transactions = 1 to 5 | 0.449 | 0.451 | -0.002 | 8.35 |
| No. of Transactions = 6 to 10 | 0.116 | 0.115 | 0.000 | 11.22 |
| No. of Transactions = 11 to 20 | 0.070 | 0.069 | 0.000 | 8.87 |
| No. of Transactions > 20 | 0.048 | 0.047 | 0.000 | 9.92 |
| Flipper | 0.568 | 0.567 | 0.001 | 13.21 |
| No. of Securities Held | 9.091 | 9.013 | 0.077** | 10.96 |
| IHS Account Age | 3.148 | 3.143 | 0.005* | 12.53 |
| New Account | 0.055 | 0.055 | 0.000 | 5.74 |
| 1 Month old | 0.067 | 0.067 | 0.000 | 9.14 |
| 2-6 Months old | 0.191 | 0.192 | -0.001 | 8.87 |
| 7-13 Months old | 0.141 | 0.141 | 0.000 | 8.87 |
| 14-25 Months old | 0.167 | 0.167 | 0.000 | 9.92 |
| > 25 Months old | 0.375 | 0.373 | 0.002** | 12.01 |

The sample size is 1,561,497 accounts. The randomization check variables are measured at the end of the month prior to the lottery allotment. *,**,*** denote significance at the 10, 5 and 1 percent levels. The flipper dummy takes the value 1 if the account had ever received an IPO and sold it in the month of receiving it.

Table 4: Effect of Winning IPO Lottery on Ownership Of IPO Stock

| | | Listing | Months Since Listing | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Dependent Variable: | | Day | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| I(Holds IPO Stock) | $\bar{y_{tr}}$ | 0.700 | 0.624 | 0.542 | 0.519 | 0.497 | 0.484 | 0.474 | 0.466 |
| | $\bar{y_{ct}}$ | 0.007 | 0.010 | 0.014 | 0.016 | 0.015 | 0.015 | 0.016 | 0.016 |
| | $\rho$ | 0.693*** | 0.613*** | 0.527*** | 0.503*** | 0.482*** | 0.468*** | 0.458*** | 0.449*** |
| Fraction of Allotment | $\bar{y_{tr}}$ | | 0.645 | 0.576 | 0.562 | 0.543 | 0.533 | 0.529 | 0.522 |
| | $\bar{y_{ct}}$ | | 0.044 | 0.058 | 0.061 | 0.061 | 0.064 | 0.065 | 0.065 |
| | $\rho$ | | 0.601*** | 0.518*** | 0.501*** | 0.481*** | 0.470*** | 0.464*** | 0.457*** |
| I(Holds Exactly IPO Allotment) | $\bar{y_{tr}}$ | | 0.587 | 0.501 | 0.477 | 0.456 | 0.442 | 0.432 | 0.423 |
| | $\bar{y_{ct}}$ | | 0.001 | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 |
| | $\rho$ | | 0.586*** | 0.499*** | 0.475*** | 0.454*** | 0.440*** | 0.429*** | 0.420*** |
| Value of IPO Shares Held (USD) | $\bar{y_{tr}}$ | | 108.818 | 84.037 | 72.500 | 70.226 | 59.546 | 53.168 | 54.717 |
| | $\bar{y_{ct}}$ | | 7.232 | 8.197 | 7.767 | 7.995 | 7.621 | 7.004 | 7.418 |
| | $\rho$ | | 101.582*** | 75.835*** | 64.727*** | 62.230*** | 51.927*** | 46.164*** | 47.296*** |
| Portfolio Weight of IPO Stock | $\bar{y_{tr}}$ | | 0.133 | 0.093 | 0.080 | 0.077 | 0.070 | 0.064 | 0.064 |
| | $\bar{y_{ct}}$ | | 0.001 | 0.002 | 0.002 | 0.002 | 0.001 | 0.001 | 0.001 |
| | $\rho$ | | 0.132*** | 0.091*** | 0.079*** | 0.075*** | 0.069*** | 0.063*** | 0.063*** |
| Mean Listing Return | | 42 | | | | | | | |
| Mean Return Over Issue Price | | | 19 | 6 | - 1 | 2 | - 5 | - 6 | - 6 |
| Mean Return Over Open Price | | | -15 | -24 | -29 | -27 | -31 | -33 | -33 |

The sample size is 1,561,497 accounts in each month. *,**,*** denote significance at 10, 5 and 1 percent levels. $\bar{y_{tr}}$ denotes the treatment group average, $\bar{y_{ct}}$, the control group average and $\rho$ the coefficient estimated from equation 1.

## Table 5: Long Run Effect of Winning IPO Lottery on Ownership Of IPO Stock

| | | Months Since Listing | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Dependent Variable: | | 0 | 1 | 4 | 8 | 11 | 12 | 13 | 16 | 20 | 24 |
| I(Holds IPO Stock) | $\bar{y_{tr}}$ | 0.639 | 0.571 | 0.513 | 0.483 | 0.465 | 0.458 | 0.452 | 0.434 | 0.401 | 0.366 |
| | $\bar{y_{ct}}$ | 0.012 | 0.014 | 0.015 | 0.016 | 0.017 | 0.017 | 0.017 | 0.017 | 0.016 | 0.015 |
| | $\rho$ | 0.628*** | 0.557*** | 0.498*** | 0.467*** | 0.448*** | 0.441*** | 0.434*** | 0.417*** | 0.385*** | 0.350*** |
| Fraction of Allotment | $\bar{y_{tr}}$ | 0.662 | 0.600 | 0.556 | 0.544 | 0.532 | 0.527 | 0.529 | 0.510 | 0.471 | 0.449 |
| | $\bar{y_{ct}}$ | 0.039 | 0.046 | 0.047 | 0.056 | 0.062 | 0.063 | 0.065 | 0.068 | 0.066 | 0.075 |
| | $\rho$ | 0.623*** | 0.554*** | 0.509*** | 0.488*** | 0.470*** | 0.464*** | 0.463*** | 0.442*** | 0.405*** | 0.374*** |
| I(Holds Exactly IPO Allotment) | $\bar{y_{tr}}$ | 0.598 | 0.526 | 0.467 | 0.434 | 0.415 | 0.409 | 0.402 | 0.385 | 0.356 | 0.323 |
| | $\bar{y_{ct}}$ | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 | 0.003 | 0.003 | 0.003 |
| | $\rho$ | 0.596*** | 0.524*** | 0.466*** | 0.432*** | 0.413*** | 0.406*** | 0.400*** | 0.383*** | 0.354*** | 0.321*** |
| Value of IPO Shares Held (USD) | $\bar{y_{tr}}$ | 119.187 | 93.533 | 57.904 | 34.810 | 22.599 | 20.450 | 18.281 | 32.914 | 33.164 | 30.496 |
| | $\bar{y_{ct}}$ | 7.081 | 7.657 | 5.570 | 4.242 | 3.066 | 2.827 | 2.625 | 4.363 | 4.555 | 5.004 |
| | $\rho$ | 112.111*** | 85.876*** | 52.34*** | 30.572*** | 19.536*** | 17.625*** | 15.658*** | 28.552*** | 28.612*** | 25.495*** |
| Portfolio Weight of IPO Stock | $\bar{y_{tr}}$ | 0.136 | 0.095 | 0.068 | 0.055 | 0.045 | 0.044 | 0.040 | 0.047 | 0.040 | 0.034 |
| | $\bar{y_{ct}}$ | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| | $\rho$ | 0.135*** | 0.093*** | 0.067*** | 0.054*** | 0.044*** | 0.043*** | 0.039*** | 0.046*** | 0.039*** | 0.033*** |
| Mean Listing Return | | 52 | | | | | | | | | |
| Mean Return Over Issue Price | | 22 | 9 | -8 | -25 | -46 | -54 | -57 | -51 | -49 | -44 |
| Mean Return Over Open Price | | -18 | -27 | -39 | -52 | -64 | -70 | -72 | -66 | -65 | -62 |

The sample includes all IPOs that occurred 24 months before the end of our portfolio data in March 2012. The sample size is 1,090,346 accounts in each month. *,**,*** denote significance at 10,5, and 1 percent levels. $\bar{y_{tr}}$ denotes the treatment group average, $\bar{y_{ct}}$, the control group average and $\rho$ the coefficient estimated from equation 1.

Table 6: Heterogeneous Winner Effects By Pre-Existing Account Characteristics

| Dependent Variable: First Day I(IPO Stock Held) | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Winner | 0.762*** | 0.649*** | 0.812*** | 0.779*** |
| # of IPOs Allotted | 0.001*** | 0.001*** | | |
| 1 to 2 IPOs | | | 0.002*** | -0.000 |
| 3 to 8 IPOs | | | 0.007*** | 0.003** |
| > 8 IPOs | | | 0.016*** | 0.009*** |
| Winner × | | | | |
| # of IPOs Allotted | -0.004*** | -0.005*** | | |
| 1 to 2 IPOs | | | -0.010*** | -0.0527*** |
| 3 to 8 IPOs | | | -0.029*** | -0.095*** |
| > 8 IPOs | | | -0.084*** | -0.165*** |
| # of Trades Made | 0.004*** | 0.000*** | | |
| 1 to 2 trades | | | 0.003*** | 0.002*** |
| 3 to 6 trades | | | 0.002*** | 0.001*** |
| > 6 trades | | | 0.012*** | 0.010*** |
| Winner × | | | | |
| # of Trades Made | -0.004*** | -0.001*** | | |
| 1 to 2 trades | | | -0.012*** | -0.031*** |
| 3 to 6 trades | | | -0.057*** | -0.096*** |
| > 6 trades | | | -0.049*** | -0.143*** |
| Fraction Past Returns > Listing Returns | -0.020*** | 0.000*** | | |
| 0.01 to 0.15 | | | 0.009*** | 0.008*** |
| 0.16 to 0.50 | | | -0.007*** | -0.007*** |
| > 0.50 | | | -0.017*** | -0.017*** |
| Winner × | | | | |
| Fraction Past Returns > Listing Returns | 0.024*** | 0.0017 | | |
| 0.01 to 0.15 | | | -0.093*** | -0.100*** |
| 0.16 to 0.50 | | | -0.047*** | -0.047*** |
| > 0.50 | | | 0.023*** | 0.018*** |
| Winner × | | | | |
| Listing Returns (%) | -0.000*** | -0.001*** | | |
| <= 0 | | | -0.212*** | -0.217*** |
| 26 to 41 percent | | | -0.059*** | -0.053*** |
| > 41 percent | | | -0.058*** | -0.056*** |
| Winner × | | | | |
| Probability of Treatment | -0.057*** | -0.051*** | | |
| 33 to 66 percent | | | -0.002 | 0.004* |
| > 66 percent | | | -0.039*** | -0.033*** |
| Controls | | | | |
| Portfolio Size | No | Yes | No | Yes |
| Age | No | Yes | No | Yes |
| IPO Share Category Fixed Effects | Yes | Yes | Yes | Yes |
| Adjusted R-squared | 0.62 | 0.63 | 0.63 | 0.64 |
| Number of observations | 1,561,497 | 1,561,497 | 1,561,497 | 1,561,497 |

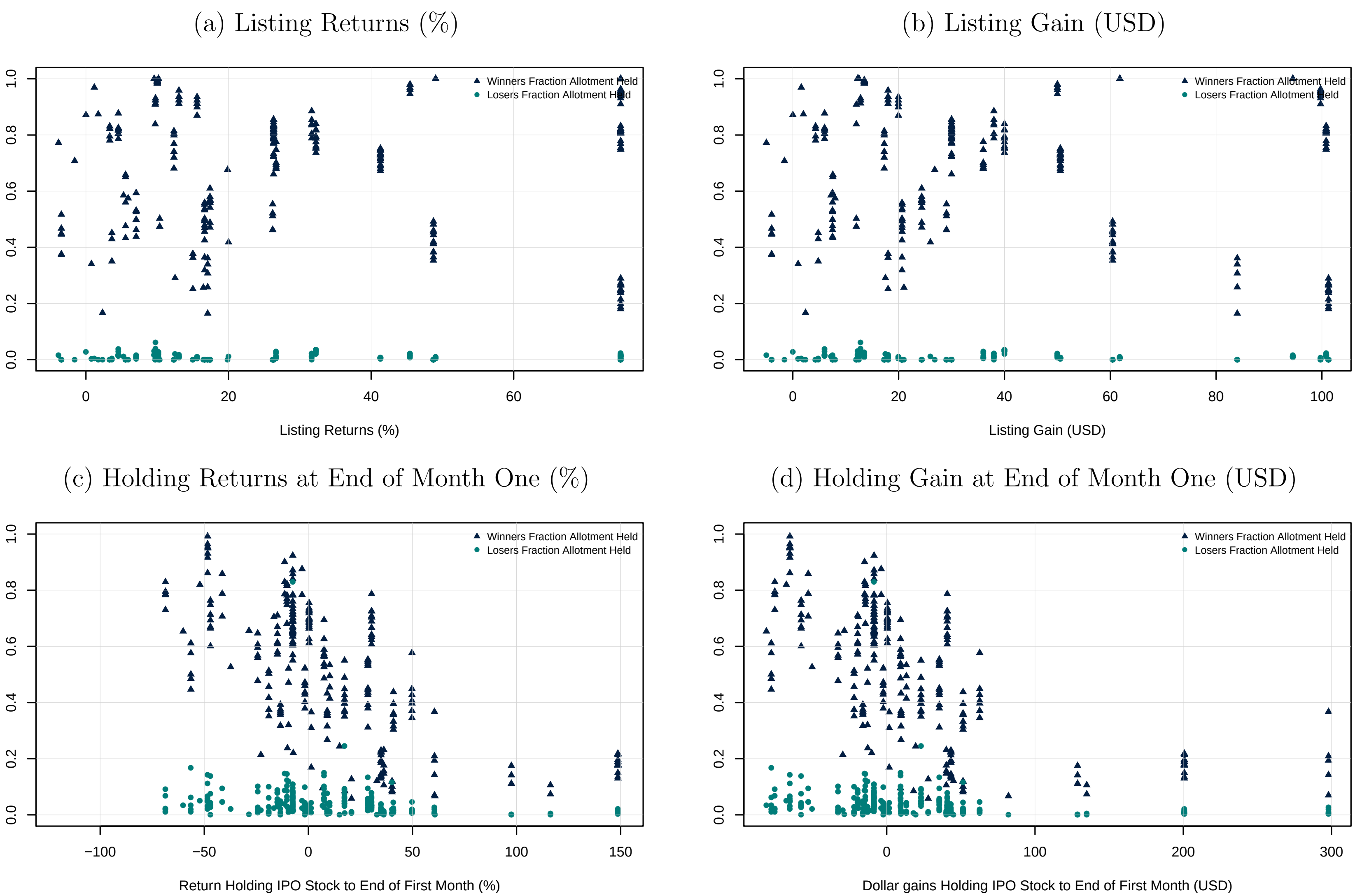
Dummies are based on quartile breakpoints of the respective distributions.

Table 7: ENDOWMENT EFFECT AND NON-IPO SMALL SIZE TRADING INTENSITY

| Dep. Var: | Months Since Listing | | | | | | |
|---|---|---|---|---|---|---|---|
| Fraction of Allotment Held | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
| | **Trade size $\leq$ IPO allotment value** | | | | | | |
| Month before allotment | 0.587 | 0.498 | 0.480 | 0.460 | 0.447 | 0.442 | 0.435 |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.005) | (0.004) | (0.004) |
| In the Month | 0.594 | 0.485 | 0.435 | 0.383 | 0.481 | 0.461 | 0.376 |
| | (0.003) | (0.004) | (0.005) | (0.014) | (0.005) | (0.006) | (0.009) |
| Upto the End of Month | 0.594 | 0.525 | 0.507 | 0.475 | 0.463 | 0.459 | 0.451 |
| | (0.003) | (0.003) | (0.003) | (0.007) | (0.007) | (0.007) | (0.007) |
| | **Trades in position size $\leq$ IPO allotment value** | | | | | | |
| Month before allotment | 0.513 | 0.408 | 0.394 | 0.386 | 0.378 | 0.376 | 0.371 |
| | (0.010) | (0.010) | (0.011) | (0.012) | (0.012) | (0.012) | (0.012) |
| In the Month | 0.466 | 0.339 | 0.325 | 0.322 | 0.355 | 0.341 | 0.303 |
| | (0.012) | (0.012) | (0.018) | (0.015) | (0.018) | (0.018) | (0.012) |
| Upto the End of Month | 0.466 | 0.367 | 0.358 | 0.347 | 0.373 | 0.394 | 0.390 |
| | (0.012) | (0.009) | (0.009) | (0.009) | (0.010) | (0.009) | (0.008) |

The sample includes all those accounts that had *at least* one trade (buy or sell) that is less than or equal to the IPO allotment value. Position size is estimated at the end of the previous month. Rows named "Upto the End of Month" do not include trades before listing month 0. Standard errors in parenthesis and all coefficients are significant at 1 percent level.

Figure 1: Fraction Allotment Held and Returns Experience




Panels (a) and (b) present estimates at the end of the first day on the y-axis and Panels (c) and (d) present estimates at the end of the first month on the y-axis.

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# Online Appendix to Endowment Effects in the Field: Evidence from India's IPO Lotteries

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**Abstract**

This online appendix contains two parts, the supplementary empirical appendix and the model appendix. The model appendix considers a range of behavioural microeconomic models of choice which have the potential to explain the endowment effects that we observe in India's IPO lotteries. We set up and solve several models, namely, several versions of the Koszegi and Rabin (2006) expectations based reference dependent utility model, including one which more closely matches the features of the real-world setting that we observe; the Weaver and Frederick (2012) reference price theory of the endowment effect; the Barberis and Xiong (2012) realization utility model; the Bordalo, Gennaioli, and Shleifer (2012) salience model; and a simple inattention model. Throughout, we discuss the features of the experimental results that are consistent and inconsistent with the predictions of these models.

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[1]We thank Nicola Gennaioli for suggesting this setup.

# A Supplementary Empirical Appendix

## A.1 Regulation governing IPO framework in India

The Securities Exchange Board of India (SEBI) Disclosure and Investor Protection Guidelines (till 2009), henceforth "DIP guidelines", SEBI Issue of Capital and Disclosure Requirements Regulation (since 2009), henceforth "ICDR regulations", and Section (19) (b) (2) of the Securities Contract Regulation Rules ("SCRR") made under the Securities Contract Regulation Act, 1956, alongside the Companies Act, 1956 govern the IPO process in India.

**Eligibility criteria**

An unlisted company may make an initial public offering (IPO) of equity shares if it meets the following conditions alongside at least 1000 investors participate in the IPO process (Rule-set 1): [2]

1. The company has net tangible assets of at least Rs. 3 crores in each of the preceding three full years (calendar years), of which not more than 50% is held in monetary assets. If more than 50% is held in monetary assets, the company has firm commitments to deploy excess monetary assets in its business.

2. The company has a track record of distributable profits (as defined in the Companies Act, 1956), for at least three years out of the immediately preceding five years.

3. The company has a net worth of at least Rs. 1 crore in each of the preceding three full years (calendar years).

4. The aggregate of the proposed issue and all previous issues in the same financial year in terms of size does not exceed five times its pre-issue networth as per the audited balance sheet of the last financial year.

[2] See Page 15-16, Section 2.2.1 of DIP guidelines, which is similar to Chapter II of the ICDR regulations, accessed on 20 April 2015. They can be accessed at `http://www.sebi.gov.in/guide/sebiidcrreg.pdf` and `http://www.sebi.gov.in/guide/DipGuidelines2009.pdf`

When a company does not fullfil these requirements, it can still undertake an IPO provided the following conditions are fulfilled (Rule-set 2):[3]

1. The issue is made through the book-building process, with *at least 50% of net offer to public* is allotted to Qualified Institutional Buyers (QIBs), failing which all subscription amount will have to be refunded.[4]

2. The minimum post-issue face value of capital will be Rs. 10 crores.

## A.2 Allocation procedure

All 54 IPOs in our sample are book-built IPOs, where the net offer to public is allocated according to the same procedure.[5] All book-built IPOs need to mandatorily achieve a minimum of 90% of the initial intended issue.[6] When a company undertakes a 100% book-built issue, the following percentage of issue will have to be initially set aside for the following investor categories:[7]

1. *Not less than* 35% of the net offer to public will be made available to *retail investors*

2. *Not less than* 15% of the net offer to public will be made available to *non-institutional investors*

3. *Not more than* 50% of the net offer to the public shall be made available for allocation to QIBs.

[3]See Page 18, Section 2.2.2 (i) - (iv) of the DIP guidelines, identical to the conditions in ICDR regulations, accessed on 20 April 2015 at `http://www.sebi.gov.in/guide/sebiidcrreg.pdf` and `http://www.sebi.gov.in/guide/DipGuidelines2009.pdf`

[4]QIBs are defined under Chapter I, definition (zd) of the ICDR regulations (Page 6). This includes mutual funds, venture capital funds (domestic and foreign), a public financial institution, banks, insurance companies and so on.

[5]See Section 11.3.5 (i) of DIP guidelines accessed on 20 April 2015.

[6]See ICDR (2009), Chapter I (14) (1), page 13

[7]The Indian regulator, SEBI, introduced the definition of a retail investor on August 14, 2003 and capped the amount that retail investors could invest at 50,000 rupees per brokerage account per IPO. This limit was increase to 100,000 rupees on March 29, 2005, and again increased to 200,000 rupees on November 12, 2010. See Section 11.3.5 (i), footnotes 480,481,482,483 on Page 216 of the DIP guidelines. "Non-institutional buyers" are all those who are not QIBs and Retail Investors - see Chapter I, definition (w) on Page 5 of ICDR regulations.

When the company does not fulfill the criteria set in Rule-set 1, then condition (3) above is *mandatory*. Further, when the company undertakes an IPO under the SCRR, the percentage requirements become 30% (retail investors), 10% (non-institutional investors) and a *mandatory* 60% to QIBs. Any shares set-aside for employees of the company is also considered to be under the "retail investor" category.[8]

Once the bidding is complete, if any of the investor categories are under-subscribed (subject to the allocation rule above), then, with full disclosure and in conjunction with the stock exchange, a company can reallocate the shares to the other investor categories.[9] However, the QIB category cannot be under-subscribed if the IPO is undertaken under Rule-set 2 or Section (19) (2) (b) of the SCRR.

While the regulation provides for alternative in the event of under-subscription, in reality, this occurs more frequently with non-institutional investors. Data from our sample of 54 IPOs show that non-institutional buyers are almost always under-subscribed. Retail investors are therefore very important to achieve the minimum of 90% of the initial intended issue, without which the IPO will fail.

In our sample of 54 IPOs, firms issue under both the SCRR and the DIP/ICRR paths. Further, the *ex-post* percentage of total final public issue to retail investors <u>can be</u> higher than the aforementioned values. This will have to be explicitly disclosed at the time of allotment of an issue. In our sample, nearly one-third of the total (final) issue size is always allotted to retail investors. Figure A.2.1 plots the percent of issue to retail investors who are *not* employees of the company.[10]

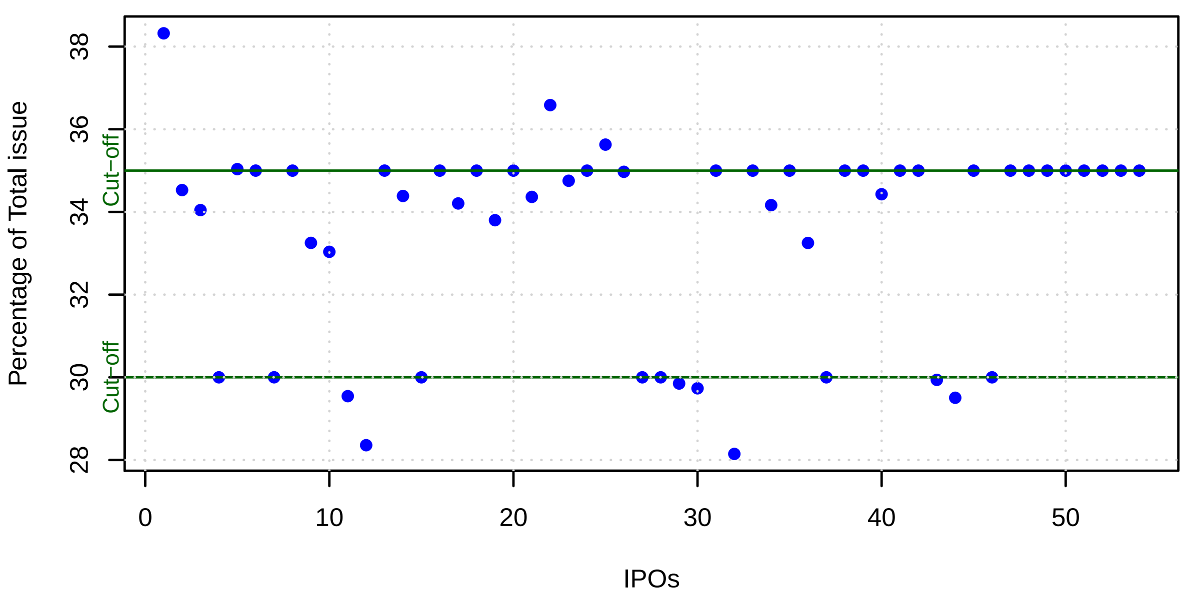
Finally, the Indian regulator, SEBI, introduced the definition of a retail investor on August 14, 2003 and capped the amount that retail investors could invest at Rs. 50,000 per brokerage account per IPO. This limit was increased to Rs. 100,000 on March 29, 2005,

[8] Note that this has been inferred from Section 11.3.5 (i), read with footnotes 480-483 on Page 216 of the DIP guidelines.

[9] See DIP guidelines (2009), Section 11.3.2 (v) read with 11.3.5 (i) and 11.3.5 (iv) (Pages 217-219).

[10] For IPOs with values less than 30% of issue, the remainder of the share comes from employees of the firm.

Figure A.2.1: Percentage of Total Issue allocated to Retail Investors (excl. employees)



and once again increased to Rs. 200,000 on November 12, 2010. This regulatory definition technically permits institutions to be classified as retail when investing amounts smaller than the limit, but over our sample period, we verify using independent account classifications from the depositories that this hardly ever occurs, and accounts for a minuscule proportion of retail investment in IPOs. We simply remove these aberrations from our analysis.

## A.3 The Probability of Treatment

Let $S$ be the total supply of shares that the firm decides to allocate to retail investors. Let $c = 1, ..., C$ index "share categories," which are integer multiples of the minimum lot size $x$ for which investors can bid. The set of possible numbers of shares for which investors can bid is therefore: $x$,$2x$,...,$Cx$.[11] Let $a_c$ be the total number of applications received for share category $c$. The total demand $D$ for an IPO with $C$ share categories is then:

$$D = \sum_{c=1}^{C} cxa_c. \tag{1}$$

Retail oversubscription $v$ is then defined as:

$$v = \frac{D}{S}. \tag{2}$$

As described in case (1) in the paper, if $v \leqslant 1$ at the ceiling price, then all investors get the shares for which they applied, and if $v > 1$, one of cases (2) or (3) will apply.[12]

In the latter two cases, the first step is to compute the allocations for each share category under a proportional allocation rule, and compare these allocations to the minimum lot size $x$.

[11] Note that the minimum lot size is also the mandatory lot size increment.

[12] At this stage it is possible that some shares will be added to the pre-specified supply to retail investors if employees and/or institutional investors participate in amounts less than they are offered. However, total firm supply is restricted by the overall number of shares that the firm decides to issue, which is fixed prior to the commencement of the application process for the IPO. Thus, it is not possible for firms to add more shares in response to greater than expected demand.

Let $J \leq C$ be the share category such that share categories $c \in [J, ..., C]$ receive proportional allocations which are greater than or equal to $x$, and share categories $c' \in [1, ..., J)$ receive proportional allocations which are less than $x$. If $J = 1$ then we are in case (2), otherwise we are in case (3).

In either case, investors in share categories $c \geqslant J$ receive a proportional allotment $\frac{cx}{v}$, and a total number of shares equalling $\sum_{c=J}^{C} \frac{cx}{v} a_c$. However, investors in share categories $c' \in [1, ..., J)$ cannot receive the minimum of $x$ shares (since $J$ is the cutoff share category, i.e., $\frac{(J-1)x}{v} < x$). Let $Z$ be the remainder of shares to be allotted, i.e.,[13]

$$Z = S - \sum_{c=J}^{C} \lfloor \frac{c}{v} x a_c \rceil. \tag{3}$$

These are the shares allocated by lottery in case (3). Note that in this lottery, the possible outcomes are winning the minimum lot size $x$ with probability $p_c$, or winning nothing with probability $1 - p_c$.

By regulation, the probability of winning in share categories $c' \in [1, ..., J)$ must be exactly proportional to the number of shares applied for, meaning that in expectation, investors will receive their proportional allocation. That is, for share categories $c' \in [1, ..., J)$:

$$\frac{p_{c'}}{p_{c'-1}} = \frac{c'x}{(c'-1)x} = \frac{c'}{c'-1}. \tag{4}$$

The combination of equation (4) and the fact that the total remaining shares are described by equation (3) gives us:

$$\sum_{c'=1}^{J-1} (p_{c'}) x a_{c'} + \sum_{c'=1}^{J-1} (1 - p_{c'}) \times 0 = Z. \tag{5}$$

Solving (5), we get that $p_{c'} = \frac{c'}{v}$ of winning exactly $x$ shares in share categories $c' \in [1, ..., J)$.

In general, the probability of winning increases proportionally with the number of share

[13] By regulation, the shares to be allotted $\sum_{c=J}^{C} \frac{c}{v} x a_c$ is rounded to the nearest integer.

lots bid for $c$, and decreases with the overall level of over-subscription $v$. This implies that the probability of winning will vary across share categories within IPOs, as well as across IPOs. In other words, there may be some self-selection of investors into share categories – that is, by applying for more share lots, they increase the probability of winning. However, conditional on two investors applying for the *same* share category in the same IPO, the investor chosen to actually receive the shares will be random. In other words, the relevant control group is the set of investors *within* the same share category who were unsuccessful in the lottery.

## A.4 Relationship between Endowment Effect and Randomized Experience

While the fact that such experienced lottery winners are so much more likely to hold the stock than similarly experienced losers is suggestive that experience does not eliminate this anomaly, it is possible that this correlation is confounded by selection effects. For example, our experience measure might be correlated with some unobserved factor that causes more experienced winners to hold the stock more than similarly experienced lottery losers (i.e., the negative effect of experience on the divergence of holdings between winners and losers are somewhat canceled out by this omitted factor when we estimate correlations). We note that this type of selection contradicts the most commonly assumed selection bias as discussed in List et al. (2003) and List (2011): those with more experience are typically thought to be *more* likely to trade in endowment experiments due to unobserved factors, because it is natural to think that to survive in a market (and gain experience) one would need to eliminate inefficient behavior such as falling prey to endowment effects. Nonetheless, we cannot rule out the presence of such unobserved factors based on correlations alone.

To make some progress on this issue, our second analysis exploits the random assignment of previous lotteries to provide a sharper comparison of whether the behavior of more experienced lottery players converges more than that of less experienced lottery players.[14] We find evidence consistent with such convergence: when we compare the behavior of randomly chosen winners and losers in future IPOs, we find that those who have previously won IPOs have smaller estimated endowment effects in the future. But, similar to the experience correlations discussed above, the rate of learning appears to be slow. Overall, the evidence from these two types of analyses suggests that while experience does substantially reduce this particular endowment effect, it seems unlikely that experience eliminates this anomaly completely.

Table A.4.1 presents the results of ten such comparisons. We focus on the 10 pairs of lotteries in our data with the largest number of applicants that applied to both lotteries within the pair. For example, the first row analyzes the behavior of the 156,120 applicants who applied to both BGR Energy Systems and Future Capital IPOs. We term the first IPO as "IPO $a$" (BGR in this case) and the second IPO as "IPO $b$" (Future Capital in this case). BGR Energy listed on January 3, 2008 and had a listing return of 66.9 percent. However, after listing BGR had a 29.9 percent loss up until the date that Future Capital listed (February 1, 2008). We are interested in whether the allotted BGR applicants show smaller endowment effects in their behavior regarding Future Capital.

To estimate whether BGR winners show a smaller endowment effect in decisions regarding Future Capital we estimate the following regression model, where the sample only includes accounts that applied to both BGR and Future Capital:

$$y_{i,c_a,c_b} = \alpha + \beta_1 \text{Win-b}_{i,c_a,c_b} + \beta_2 \text{Win-b}_{i,c_a,c_b} * \text{Win-a}_{i,c_a,c_b} + \beta_3 \text{Win-a}_{i,c_a,c_b} + \gamma_{c_a,c_b} + \epsilon_{i,c_a,c_b} \quad (6)$$

$y_{i,c_a,c_b}$ is an indicator for whether account $i$ in share category $c_a$ of IPO $a$ and in share

[14] While our main comparison of lottery winners and losers constitutes a randomized experiment, our comparison of past winners and losers in future lotteries has one potentially important selection issue: the choice of whether to participate in future IPOs may depend on previous experience. We discuss how this type of selection might affect this set of experience estimates.

category $c_b$ of IPO $b$ holds the IPO $b$ stock at the end of the first month after IPO $b$ was listed (i.e. at the end of February 2008 in the case of the BGR/Future Capital pair represented in the first row. Note that a given account can only appear in exactly one share category in IPO $a$ and one share category in IPO $b$ because an account can only apply once to a given IPO. Win-b$_{i,c_a,c_b}$ and Win-a$_{i,c_a,c_b}$ are indicators for whether account $i$ was allocated in IPO $b$ and IPO $a$ respectively. $\gamma_{c_a,c_b}$ are fixed effects for each possible pair of share category combinations across IPOs $a$ and $b$. We include these fixed effects to control for any factors that are common to people who chose to apply to given share categories in IPOs $a$ and $b$.

We are primarily interested in the coefficient $\beta_2$, which tells us the difference in the estimated endowment effect in IPO $b$ based on whether the account won the lottery in IPO $a$. Column (8) of Table A.4.1 reports $\beta_2$ for the ten largest pairs of IPOs in terms of the number of applicants who applied to both. We would expect $\beta_2$ to typically be negative, because observing the performance of the IPO stock after listing should cause greater convergence in the behavior of winners and losers in the next IPO.[15] Consistent with this, we estimate negative coefficients in nine of the ten examples studied here. On the other hand, the estimated coefficients are small, suggesting that an account would require a very large number of these experiences before the endowment effect was eliminated (similar to our conclusion in the previous analysis).

It is important to note that there are two potential mechanisms underlying our negative estimates of $\beta_2$. The first is that winning shares in IPO $a$ causes a given account to exhibit the endowment effect less in a future IPO (i.e. a causal effect of experience). The second is that the types of players who choose to apply to IPO $b$ after winning shares in IPO $a$ are differentially selected to be the type who have lower endowment effects (i.e. a selection effect). Previous studies, such as List (2011), focus on separating these two effects, but this is difficult in our setting as the choice to apply for a future IPO is endogenous.

[15] For example, lottery winners who experience a negative open return should sell future allotments faster, thus reducing the convergence. Similarly, lottery losers who observe the IPO stock having a positive listing return should be more likely to purchase the stock on the open market.

However, we argue that in this particular analysis the joint effect is a primary object of interest; it tells us whether the two forces of investors learning from experience as well as the force of experiences driving some investors out of the market, lead to lower market anomalies (such as the endowment effect) over time. If winning previous lotteries makes an account more likely to apply (which we show in Anagol et al. (2015)), then these results would suggest that there will be a modest reduction in endowment effects under the selection mechanism as well. For example, suppose the entire difference in behavior of past winners and losers in future IPOs is due to selection, this would mean that winning past lotteries induces a selection of investors who exhibit lower anomalies in the future.

Table A.4.1: Effect of Winning Previous Lotteries on Propensity to Hold Future IPO Allocations

| IPO A | | | | IPO B | | | Differential |
|---|---|---|---|---|---|---|---|
| Name | Listing Date | Listing Return (%) | Open Return (%) | Name | Listing Date | Observations | Winner Effect |
| BGR | 1/3/2008 | 66.88 | -29.86 | Future Capital | 2/1/2008 | 156120 | -0.024*** |
| | | | | | | | [0.003] |
| Career Point | 10/6/2010 | 48.71 | -15.92 | P&S Bank | 12/30/2010 | 34488 | -0.026*** |
| | | | | | | | [0.009] |
| Omaxe | 8/9/2007 | 29.03 | -27.54 | BGR | 1/3/2008 | 34574 | -0.010 |
| | | | | | | | [0.006] |
| Vishal Retail | 7/4/2007 | 75.01 | 187.50 | BGR | 1/3/2008 | 49150 | -0.022*** |
| | | | | | | | [0.007] |
| Omaxe | 8/9/2007 | 29.03 | -35.48 | Future Capital | 2/1/2008 | 34418 | 0.011* |
| | | | | | | | [0.006] |
| Vishal Retail | 7/4/2007 | 75.01 | 187.50 | Future Capital | 2/1/2008 | 46816 | -0.025*** |
| | | | | | | | [0.007] |
| Meghmani | 6/28/2007 | 75.00 | -14.44 | BGR | 1/3/2008 | 29304 | -0.080*** |
| | | | | | | | [0.008] |
| Omnitech | 8/14/2007 | 75.00 | -3.67 | BGR | 1/3/2008 | 29276 | -0.038*** |
| | | | | | | | [0.010] |
| BGR | 1/3/2008 | 66.88 | -10.32 | P&S Bank | 12/30/2010 | 48469 | -0.001 |
| | | | | | | | [0.007] |
| Future Capital | 2/1/2008 | 36.47 | -81.82 | P&S Bank | 12/30/2010 | 54337 | -0.008 |
| | | | | | | | [0.007] |

The dependent variable is the fraction of the winning allotment held. The full sample includes all applicants for 196 shares in BGR that also applied for 128 shares in Future Capital. Standard errors in brackets and mean of the dependent variable for lottery losers in the parentheses. *,**,*** denote significance at the 10, 5 and 1 percent levels.

## A.5 Alternative Explanations for the Endowment Effect

**Wealth Effects and House Money Effects.** Thaler and Johnson (1990) introduced the idea that decision makers may be willing to take more risk when they have recently experienced a gain. In our setting, lottery winners experience a 42 percent gain on their IPO stock allotment upon listing, whereas lottery losers (most likely) do not experience a large gain on the cash returned to them as part of their endowment. Under the house money effects explanation, lottery winners choose to hold the IPO stock because they are more willing to take risk after experiencing the listing gain (i.e. they view holding the stock as "gambling with house money"). Note that a traditional wealth effect would deliver the same result, although the wealth would presumably be spread across all of the securities the investor holds rather than increasing the allocation to the IPO stock alone.

One prediction of the wealth effects/house money hypothesis is that we would expect lottery winners tendency to hold the stock to *increase* as they experience greater gains on the IPO stock (because the amount of house money earned is greater in this case). Contrary to this, we find that the endowment effects are typically smaller as the gains experienced in the IPO stock increase. Figure 1 (a) and (b), in the main paper, shows little relationship between the listing gain earned on the stock and the tendency for the winners to hold the stock; house money effects would predict that those with the largest listing gains should be most likely to take the risk of holding the IPO stock longer. And, moving forward in time, Figures 1 (c) and (d) in the paper show that the endowment effects get substantially smaller as returns on the IPO stock in the first month increase.

**Monetary Transaction Costs.** One possible explanation for the divergence we find between lottery winners and losers holding the IPO stock is that monetary transaction costs make it unprofitable for lottery winners to sell the stock, and simultaneously make it unprofitable for lottery losers to buy the stock. Note that under this explanation, both winners and losers have the same optimal holding levels, but the cost of getting to that optimal holding level outweighs the benefits of arriving at the optimal holding level.

In terms of monetary transaction costs, there are two primary types of costs to consider: (1) brokerage commissions, and (2) securities transactions taxes.[16] Our data does not include information on brokerage commissions costs, and we are not aware of any representative datasets on commissions for Indian equity accounts. However both the Bombay and National Stock Exchanges specify that brokers may not charge more than 2.5 percent of the valuation of a transaction as a brokerage fee. In our sample the average IPO allotment is worth 150 USD, so the commissions to buy or sell the full allotment are on average less than 3.75 USD. In reality commissions are typically much lower than the statutory maximums because of competition amongst brokers. We hand collected brokerage commissions from twenty major retail brokerage firms over our sample period (2007-2012) and found the commissions to vary between .3 to .9 percent of the transaction value, much less than the statutory maximum of 2.5 percent (Table A.5.1). Securities transaction taxes are an additional 14.5 basis points (Mohanty, 2011). Given these estimates it seems unlikely that monetary transactions costs would cause such a large divergence between the holdings of lottery winners and losers of the IPO stock.

**Multiple Applications Per Household.** It is worth noting here that regardless of the number of applications that households put in, if they only make their buying or holding decisions based on a comparison of their valuation of the stock versus the market price (as they would in the simplest expected utility model), then they should all end up owning the same number of shares after the stocks lists. This is because the randomization of share allocations is orthogonal to valuations, meaning that the simplest expected utility model will continue to predict no endowment effect regardless of whether households are submitting multple applications or not.

A further possibility to consider is that households have some target number of shares, and

[16] In addition to the direct securities transaction tax (12.5 basis points paid to central government during our sample period) there are three additional taxes charged at the time of transaction: a service tax on brokerage (10.3 percent of the brokerage commission paid to central government), a stamp duty (1 basis point of transaction value paid to state government), and a SEBI turnover fee (1 basis point of transaction value paid to stock market regulator).

this target is lower than the total amount they would be allotted across all their applications. For example, suppose that all households decide that they would like to hold one allotment, and pursue an application strategy consistent with this desire. To fix ideas, consider an example where there are 400 applications to a given category that come from 200 households, with 2 applications per household. Let the probability of winning the IPO be $p$. Given the randomization, this scenario implies that there will be $200p^2$ households with two winning accounts, $400p(1-p)$ households with one winning account and one losing account, and $200(1-p)^2$ households with no winning accounts. With a one share per household target, we might see an endowment effect because households will tend to hold in the accounts in which they won, and not purchase in the accounts in which they lost. More specifically, $200p^2$ households with two wins will each sell one share, $400p(1-p)$ households will hold the share they won, and do nothing else on the losing application, and the $200p(1-p)$ households who lost will buy one share each. The total fractions conditional on winning and losing will therefore exhibit an "endowment effect."

The key problem with this explanation is that the randomization of the lottery will naturally also produce many households where none of the accounts are allotted ($200p(1-p)$ in the above example), yet these households should have the same target number of shares to hold as households that were allotted (recall that winning and losing the lottery is orthogonal to target share demands). If this target share explanation is correct then we should observe many loser accounts buying on the first day, especially when the probability of winning is low on average (as it is in our data, $p = 0.36$, see Table 2). However, the fact that lottery losers do not in general buy the IPO stock is strongly inconsistent with this kind of multiple applications per household theory explaining our results.

**Flipping Incentives.** In the United States, IPO shares are typically rationed to brokerage clients who have provided large value to the brokerage firm. There is substantial anecdotal and empirical evidence to suggest that brokerages discourage investors from quickly selling their allotted shares, in particular by threatening that "flippers" will be denied future IPO allocations (Aggarwal, 2003). Thus, in the United States, it is possible that allottees of IPOs choose to hold the stock much longer than statistically similar non-allottees because they believe selling the stock will reduce their chances of being allotted future IPOs.

A few factors make this explanation less plausible in the Indian setting. First, Table 3 in the paper shows that lottery winners and losers are balanced in terms of their tendency to quickly sell IPO stocks in the past; the fraction of lottery winners who sold an IPO in the first month after allotment (56.8 percent) is almost exactly equal to the fraction of lottery losers who sold an IPO in the first month after allotment (56.7 percent). If the lottery process penalized "flippers" we would expect lottery winners to be less likely to have quickly sold an IPO in the past. Second, the lottery process is publicly advertised after allocations are made (i.e. the fraction of allottees randomly chosen appears in newspaper articles etc.), and it is generally common knowledge that winners are chosen at random; therefore, it is not clear why investors would assume that selling their shares quickly would hurt them in future allocations.

**Tax Motivated Behavior.** Two distinct tax issues might influence the holding behavior of lottery winners in the Indian context. First, the capital gains tax rate changes from 15 percent if a holding is sold within a year (a short term gain/loss) to zero if the holding is sold after one year. Investors holding the IPO stock at a gain might therefore have an incentive to wait until after one year of allotment to avoid paying the short term capital gains tax. Under this hypothesis we would expect the endowment effect estimates to drop substantially between the twelfth and thirteenth month after allotment. However, Table 5 in the paper shows only a small drop in the divergence between winner and loser holdings going from the twelfth to thirteenth month.

The second issue is that in India short term (less than 1 year) losses on stocks can be applied to short term gains on stocks to reduce capital gains tax liability.[17] Constantinides (1984) notes that under these types of tax incentives, and the presence of transactions costs,

[17]During the period of our study short term capital gains were taxed at 15 percent. There was no long term (greater than one year) capital gains tax, and therefore no opportunity for long term tax loss offsets.

investors should slowly realize their losses with the volume of sales peaking right before the end of the fiscal year. This might give lottery winners an incentive to generally hold their shares that have experienced losses until the end of the Indian fiscal year (March 31), and then sell them in right before the end of the fiscal year. Under this hypothesis we would expect the divergence between buyers and sellers to drop in March as lottery winners sell their losses on IPO stocks as tax offsets.

To investigate this hypothesis we regress a dummy for whether an account holds the IPO stock on an indicator for being a winner in the lottery, a full set of interactions of the winner indicator with the calendar month of the year, and a full set of interactions between the winner indicator and the number of months since the IPO was allotted. The regression also includes the calendar month and number of months since IPO indicators separately. We include the month since IPO indicators as the treatment effects have a strong pattern of declining after allotment, and we want to separately analyze the relationship between certain calendar months from any correlation between calendar month and time since allotment.

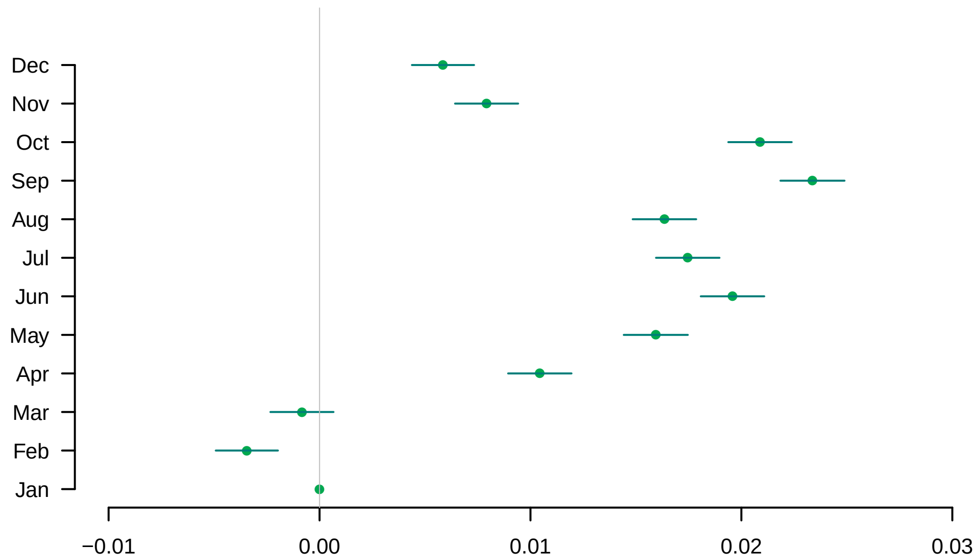
Figure A.5.1 plots the calendar month interactions with the winner variable along with 95 percent confidence intervals. These coefficients show how much smaller or larger the winner effect on holding the IPO stock is, based on the calendar month of the observation. The omitted calendar month is January. Consistent with the tax hypothesis, we see that the months January, February, and March do have the lower estimated endowment effects relative to the other months of the year. Quantitatively, however, this effect is quite small, ranging from 1 to 2 percentage points. Given that the overall propensity of winners to hold the stock relative to losers is between 45 and 55 percent over the first twelve months after the allotment, the results suggest it is unlikely that tax offset motivated behavior explains a large fraction of the endowment effect in this setting.

Table A.5.1: Monetary Transaction Costs: Brokerage Charges in India

| | A/c opening charge (Rs.) | Annual maintenance charge (Rs.) | Brokerage (delivery) Paise (%) | Brokerage (Intra-day) Paise (%) |
|---|---|---|---|---|
| Angel Broking | 390 | 300 | 30 | 6 |
| Bonanza | 600 | 275 | 50 | 5 |
| Canmoney | 200 | 250 | (0.35) | (0.1) |
| Geojit BNP Paribas | 800 | 400 | 30 | 3 |
| HDFC securities | 999 | 550 | 25 (0.5) | 25 (0.05) |
| ICICI Direct | 975 | 450 | (0.55) | (0.05) |
| IDBI Paisabuilder | 700 | 350 | (0.5) | (0.08) |
| Indiabulls | 1350 | 450 | (0.3) | (0.05) |
| India Infoline | 750 | 0 | 50 | 5 |
| Kotak Securities | 750 | 50 | 59 | 6 |
| Motilal Oswal | 550 | 900 | (0.5 – 0.9) | (0.25 – 0.40) |
| Networth Direct | 200 | 440 | (0.3) | (0.03) |
| Reliance Money | 950 | 210 | (0.3) | (0.035) |
| Religare | 499 | 300 | 30 | 3 |
| SBI | 500 | 386 | 75 | 5 |
| Sharekhan | 750 | 441 | (0.5) | (0.1) |
| SMC India | 499 | 0 | 30 | 3 |
| Ventura | 1000 | 400 | 45 | 5 |
| Way2Wealth | 350 | 332 | 0.5 | 0.05 |
| 5Paisa | 500 | 250 | 0.25 | 0.05 |

These numbers are for online "cash" trades only. Advalorem charges in percent are in parenthesis. Flat charges are in "paise" (1/100th of a rupee).

Figure A.5.1: Endowment Effects By Month of the Year




## A.6 Estimate of the First Day Endowment Effect

To estimate the short-run endowment effect in this setting, we adopt an algorithm to determine whether or not a sale of a stock happened on the day the stock began trading on the market. We use the daily high and low price data in the month of listing, and classify a stock to have potentially traded on days where the selling price falls within that range. This provides us with the likelihood of trade having happened on specific days of the listing month. For example, if an investor sells a stock at Rs. 30 per stock, and this is within the high-low range on three specific days of the listing month in which this trade happened, then the likelihood of the trade is 0.33 for each of these days of the month. In order to be most conservative with this classification, we further classify first-day sale (for the treatment group) and first-day purchase (for the control group) as follows: If $0 < Pr(\text{Sale on first day}) < 1$, then we assume that they sold on the first day and set the probability of sale on the first day to 1. This over-estimates the likelihood of sale on the first-day for the treatment group.

If $0 < Pr$(Purchase on First Day) $< 1$, then we assume that they purchased on the first day and set the probability of purchase to 1. This over-estimates the likelihood of purchase on the first day for the control group. The difference between the conservative estimates of the (weighted) average holding propensity for the treatment group and the (weighted) average purchase propensity for the control group on the first-day of trading provides us the estimate of the first-day endowment effect.

Other measures of the endowment effect such as the fraction of allotment and Value of IPO Shares Held in USD are less precise as they require additional assumptions. For example, suppose we want to calculate the fraction of allotment held at the end of the first day for an investor who was allotted 50 shares and sold 20 shares during the month. The algorithm requires assumptions to determine which of the days 2/5th of the allotted shares were sold. These assumptions, for instance, will involve choosing whether they were sold fully in one trade or in multiple trades of different lot size. This is important as the selling price used in the identification algorithm will change depending on the size assumptions and hence will impact the likelihood of trade on a given day. Similarly, measures of the value of IPO shares held will be affected by such auxiliary assumptions, and the portfolio weight of the IPO stock will require assumptions about holdings in the portfolio as well. To simplify the presentation of results, we choose not to report these additional measures of the endowment effect (rows 2 to 5 of Table 4) for the listing day.

## A.7 Appendix Tables and Figures

Table A.7.1: IPO Characteristics

| | 2007 | 2008 | 2009 | 2010 | 2011 | All |
|---|---|---|---|---|---|---|
| **IPOs in sample** | | | | | | |
| Number of IPOs in sample | 12 | 10 | 2 | 22 | 8 | 54 |
| Percentage of all IPOs in India | 12.04 | 31.58 | 11.76 | 32.84 | 20.51 | 22.13 |
| Value of IPOs in sample ($ bn) | 0.28 | 0.42 | 0.03 | 1.58 | 0.34 | 2.65 |
| Percentage of total value of IPOs in India | 3.00 | 8.77 | 0.72 | 11.01 | 24.62 | 7.71 |
| Percentage issued (Retail investors excl. employees) | 33.01 | 34.33 | 34.88 | 32.71 | 35.00 | 33.50 |
| Over-subscription ratio | 21.95 | 12.63 | 2.11 | 10.10 | 6.72 | 12.06 |
| No. of randomized share categories ("Experiments") | 109 | 55 | 2 | 177 | 40 | 383 |
| Total no. of share categories | 178 | 152 | 28 | 398 | 227 | 983 |
| **No. of IPOs from different sectors** | | | | | | |
| Technology | 1 | 1 | 0 | 2 | 0 | 4 |
| Manufacturing | 8 | 6 | 2 | 12 | 3 | 31 |
| Other Services | 2 | 3 | 0 | 8 | 4 | 17 |
| Retail | 1 | 0 | 0 | 0 | 1 | 2 |

Table A.7.2: Endowment Effect and Non-IPO Trading Intensity

| Dep. Var: | Months Since Listing | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| I(Holds IPO Stock) | 0 | 1 | 4 | 8 | 11 | 12 | 13 | 16 | 20 | 24 |
| | **0 Non-IPO transaction** | | | | | | | | | |
| In the Month | 0.723 | 0.668 | 0.519 | 0.523 | 0.491 | 0.478 | 0.459 | 0.418 | 0.358 | 0.369 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Upto the End of Month | 0.723 | 0.646 | 0.600 | 0.580 | 0.539 | 0.527 | 0.521 | 0.494 | 0.449 | 0.410 |
| | (0.001) | (0.002) | (0.003) | (0.003) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| | **1 Non-IPO transaction** | | | | | | | | | |
| In the Month | 0.738 | 0.691 | 0.653 | 0.439 | 0.304 | 0.350 | 0.396 | 0.491 | 0.428 | 0.362 |
| | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.003) | (0.003) | (0.002) | (0.002) | (0.002) |
| Upto the End of Month | 0.738 | 0.763 | 0.737 | 0.596 | 0.582 | 0.563 | 0.563 | 0.546 | 0.477 | 0.433 |
| | (0.001) | (0.001) | (0.002) | (0.005) | (0.006) | (0.006) | (0.006) | (0.006) | (0.007) | (0.007) |
| | **2 to 5 Non-IPO transactions** | | | | | | | | | |
| In the Month | 0.569 | 0.475 | 0.408 | 0.343 | 0.383 | 0.325 | 0.352 | 0.422 | 0.496 | 0.313 |
| | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Upto the End of Month | 0.569 | 0.577 | 0.648 | 0.659 | 0.641 | 0.636 | 0.629 | 0.614 | 0.587 | 0.544 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| | **6 to 10 Non-IPO transactions** | | | | | | | | | |
| In the Month | 0.517 | 0.410 | 0.324 | 0.311 | 0.287 | 0.295 | 0.303 | 0.357 | 0.354 | 0.270 |
| | (0.002) | (0.002) | (0.002) | (0.003) | (0.004) | (0.004) | (0.004) | (0.004) | (0.003) | (0.003) |
| Upto the End of Month | 0.517 | 0.470 | 0.496 | 0.522 | 0.516 | 0.508 | 0.502 | 0.489 | 0.477 | 0.447 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| | **11 to 20 Non-IPO transactions** | | | | | | | | | |
| In the Month | 0.518 | 0.390 | 0.285 | 0.278 | 0.290 | 0.276 | 0.281 | 0.343 | 0.318 | 0.232 |
| | (0.003) | (0.003) | (0.003) | (0.004) | (0.005) | (0.005) | (0.005) | (0.004) | (0.004) | (0.004) |
| Upto the End of Month | 0.518 | 0.425 | 0.408 | 0.434 | 0.434 | 0.429 | 0.425 | 0.413 | 0.398 | 0.380 |
| | (0.003) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| | **$>$ 20 Non-IPO transactions** | | | | | | | | | |
| In the Month | 0.471 | 0.336 | 0.238 | 0.254 | 0.249 | 0.233 | 0.227 | 0.296 | 0.259 | 0.190 |
| | (0.004) | (0.004) | (0.004) | (0.005) | (0.006) | (0.006) | (0.007) | (0.005) | (0.005) | (0.005) |
| Upto the End of Month | 0.471 | 0.384 | 0.317 | 0.293 | 0.291 | 0.288 | 0.286 | 0.281 | 0.272 | 0.252 |
| | (0.004) | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |

The sample includes all IPOs that occurred 24 months before the end of our portfolio data in March 2012. The total sample size is 1,090,346 accounts in each month. Standard errors in parenthesis and all coefficients are significant at 1 percent level.

Table A.7.3: Comparison of Endowment Effect Sizes With Previous Studies

| Study | Sample | Good A | Good B | Endowment Effect (%) |
|---|---|---|---|---|
| *Panel A: Low Experience Samples* | | | | |
| Current Study | Retail Investors (1st IPO Allotment) | IPO Stock | Cash | 77 |
| Current Study | Retail Investors (1 to 2 IPO Allotments) | IPO Stock | Cash | 72 |
| List (2003) | Card Show Non-Dealers | Baseball Ticket | Baseball Certificate | 60 |
| List (2003) | Pin Show Inexperienced Consumers | Valentine's Pin | St. Patrick Day's Pin | 64 |
| List (2003) | Card Show Non-Dealers | Autographed Photo | Autographed Baseball | 29 |
| List (2011) September Round | Inexperienced Card Show Attendees | Sports Memorabilia | Sports Memorabilia | 73 |
| List (2011) December Round | Inexperienced Card Show Attendees | Sports Memorabilia | Sports Memorabilia | 79 |
| List (2011) February Round | Inexperienced Card Show Attendees | Sports Memorabilia | Sports Memorabilia | 59 |
| *Panel B: High Experience Samples* | | | | |
| Current Study | Retail Investors (3 to 8 IPO Allotments) | IPO Stock | Cash | 67 |
| Current Study | Retail Investors (>= 8 IPO Allotments) | IPO Stock | Cash | 60 |
| List (2003) | Card Show Dealers | Baseball Ticket | Baseball Certificate | 9 |
| List (2003) | Pin Show Experienced Consumers | Valentine's Pin | St. Patrick Day's Pin | 7 |
| List (2003) | Card Show Dealers | Autographed Photo | Autographed Baseball | 9 |
| List (2011) December Round | Experienced Card Show Attendees | Sports Memorabilia | Sports Memorabilia | 31 |
| List (2011) February Round | Experienced Card Show Attendees | Sports Memorabilia | Sports Memorabilia | -10 |

Figure A.7.1: IPO Frequency

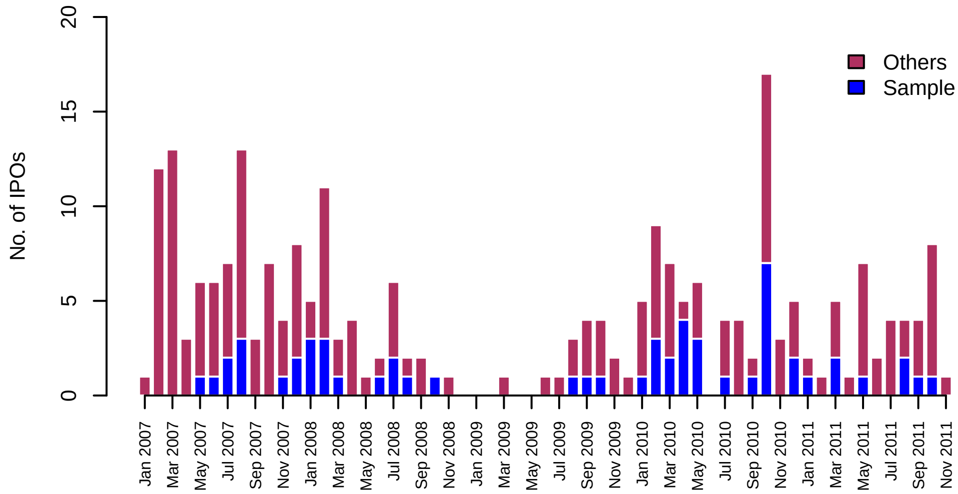


Figure A.7.2: Long-Run Holding Returns on IPOs in India

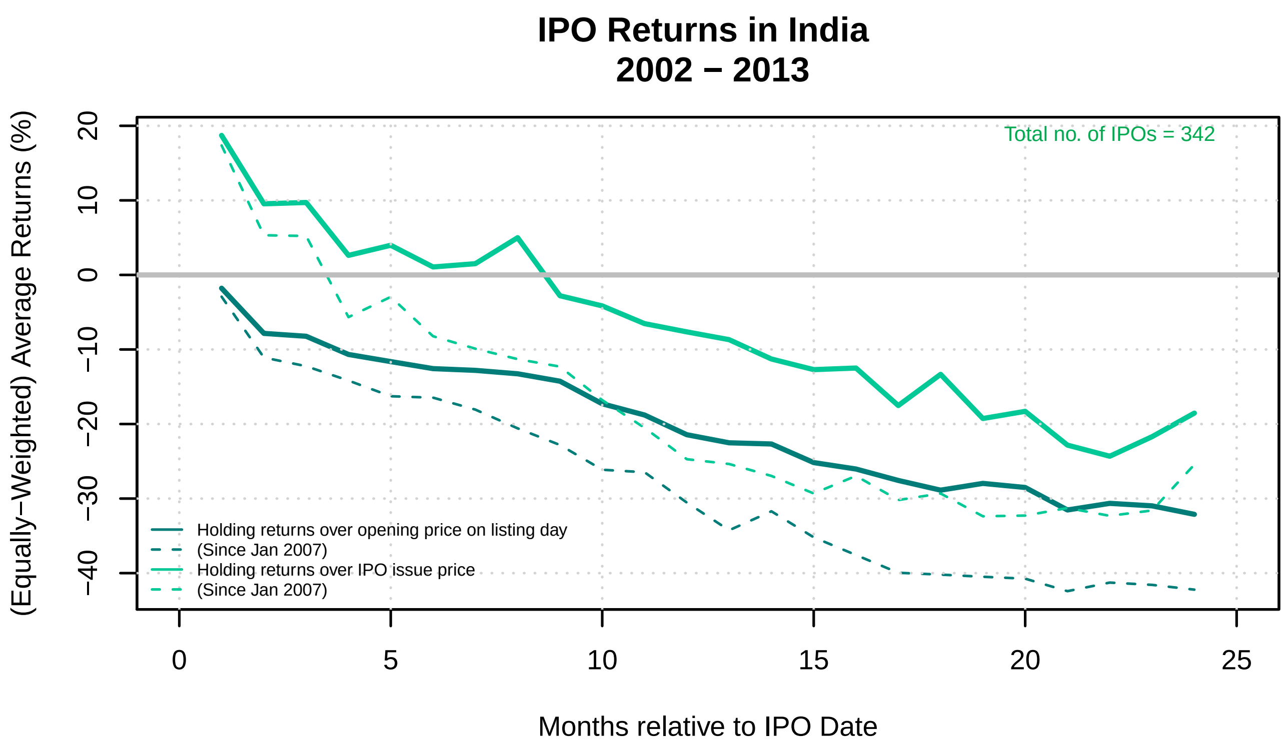
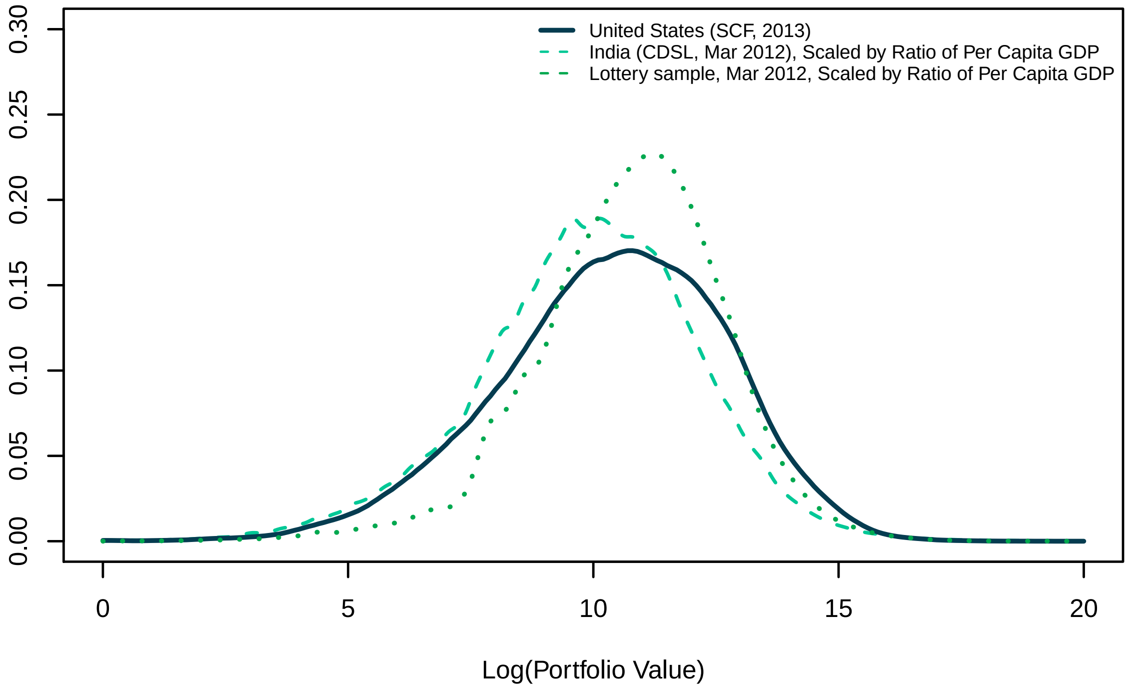


Figure A.7.3: Comparison of Lottery Sample to India and the United States

(a) Portfolio value distribution




(b) Histogram of number of trades

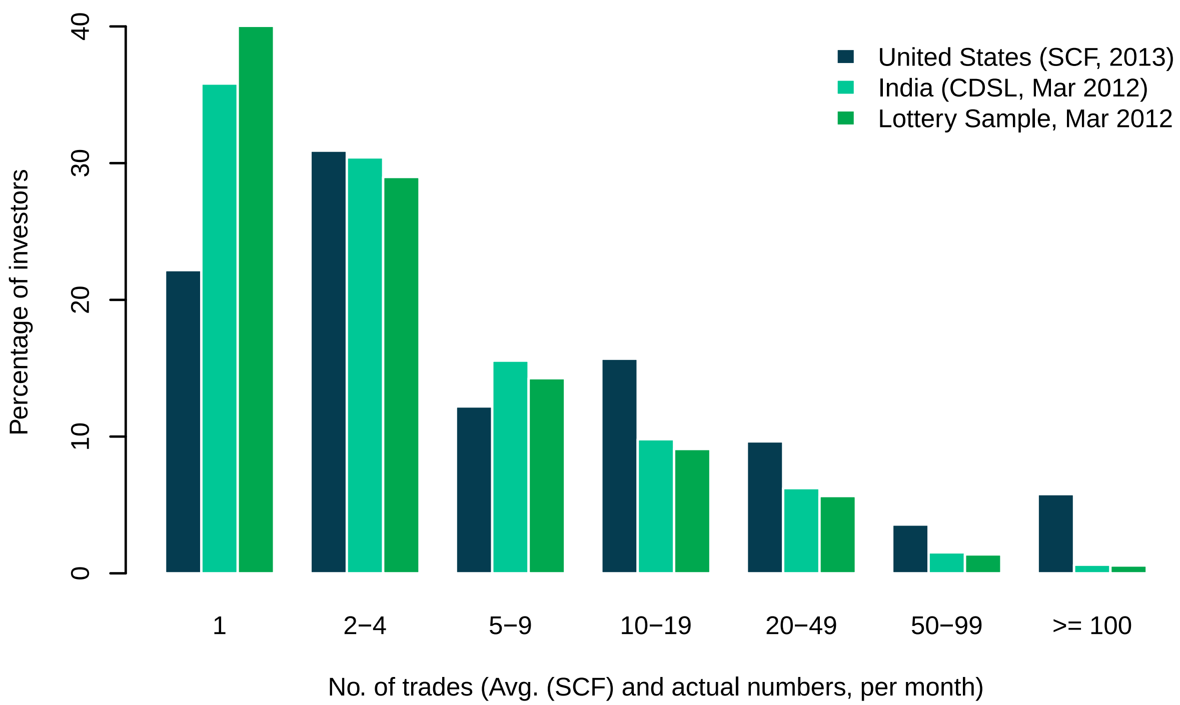
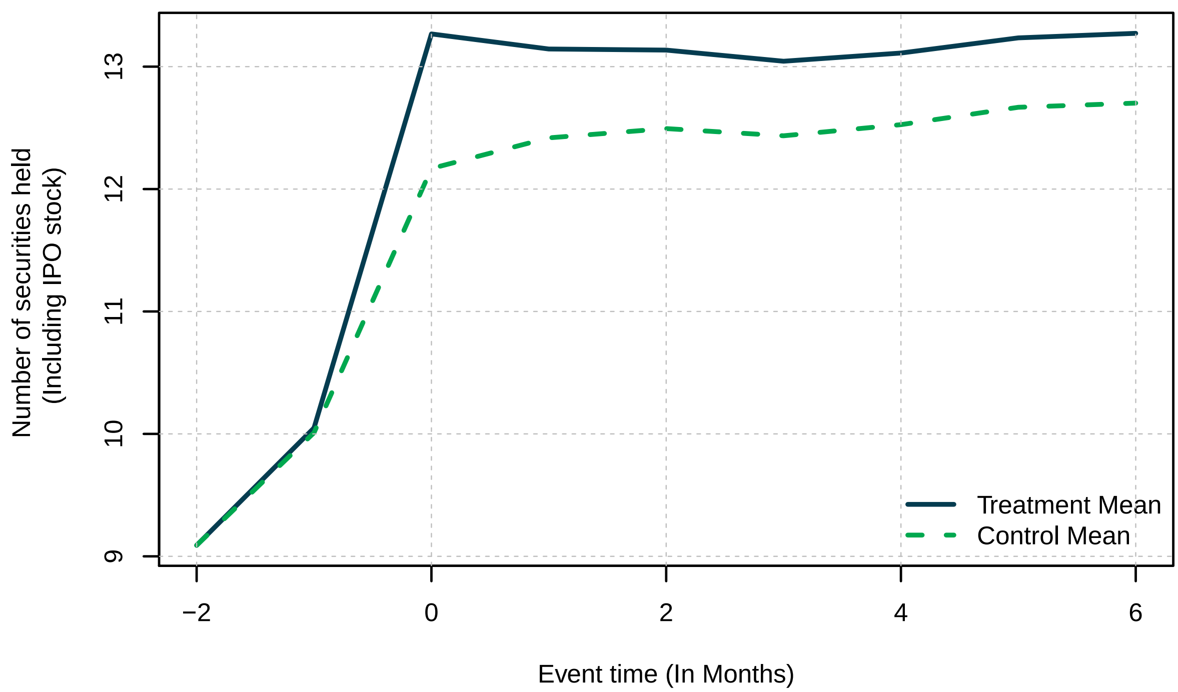


Figure A.7.4: Number of Securities Held (Including IPO Stock)



# B Model Appendix

In this model appendix, we consider a range of behavioral microeconomic models of choice which have the potential to explain the endowment effects that we observe in India's IPO lotteries. We set up and solve several models, namely, several versions of the Koszegi and Rabin (2006) expectations based reference dependent utility model, including one which more closely matches the features of the real-world setting that we observe; the Weaver and Frederick (2012) reference price theory of the endowment effect; the Barberis and Xiong (2012) realization utility model; the Bordalo, Gennaioli, and Shleifer (2012) salience model; and a simple inattention model. Throughout, we discuss the features of the experimental results that are consistent and inconsistent with the predictions of these models.

We begin by presenting three models of an agent with reference dependent utility, where the agent's recently formed expectations of future outcomes constitute their reference points as in Koszegi-Rabin (2006).

# C Expectations Based Reference-Dependent Utility Models

As in Koszegi-Rabin (2006), an agent's reference points in these models are determined by his expectations of outcomes, which in turn are based on his planned actions. Naturally, his planned actions also depend on his expectations of outcomes. This dual dependence gives rise to the need for an equilibrium concept. We begin by solving for the personal equilibrium (PE), which involves identifying conditions under which the agent has no incentive to deviate from a particular planned action of interest, conditional on the plan generating a particular expectations-based reference point. In certain cases, we go further and discuss the conditions under which the plan is also a preferred personal equilibrium (PPE), i.e., the plan which delivers the highest level of utility of all possible PEs.

Our approach in all cases is to enumerate all possible plans of action open to the agent, and the expectations associated with each such plan. We then solve for the conditions/parameter values under which certain plans dominate others, using the PE and PPE concepts. We are of course most interested in the conditions under which the plan corresponding to the "endowment effect" which we observe in our field experiment, is a PE/PPE.

All three variations of the model which we consider share the same basic preference specification, namely:

- The agent has expectations based reference dependent preferences with loss-aversion:

  $$u(z|r) = m(z) + \mu(m(z) - m(r)).$$

  In the above, $m(.)$ is consumption utility, and $\mu(.)$ is gain-loss utility relative to the referent, $r$.

- We assume piecewise linear gain-loss utility, i.e.,

  $$\mu(y) = \begin{cases} \eta \cdot y & \text{if } y \geq 0 \\ \eta \cdot \lambda \cdot y & \text{if } y < 0 \end{cases},$$

  where $\lambda$ is the degree of loss aversion (we assume $\lambda > 1$).

- We also make a set of additional simplifying assumptions. First, we assume that $\eta = 1$, so:

  $$\mu(y) = \begin{cases} y & \text{if } y \geq 0 \\ \lambda \cdot y & \text{if } y < 0 \end{cases}.$$

  Second, we assume that $m(z) = z$. Third, we assume that all gambles that the agents face are binary, as we describe in each case below.

We begin with the setup of Ericson and Fuster (2011), move on to considering the setup of

Sprenger (2015), and conclude this section with a more elaborate model that more accurately captures features of our real-world setting.

## C.1 Ericson and Fuster (2011) Model

Ericson and Fuster (2011) model the typical participant in an endowment effects experiment within the exchange paradigm. In their experimental application, an agent is randomly assigned a mug or a pen, and then expects, with probability $b$, that they will be given the opportunity to trade the object later. In their experiment, they manipulate this probability $b$, and observe the associated rates of exchange of the mug and the pen.

We use the identical set up to theirs in this version of the model, but simply re-label the objects "stock" (to represent the allocation of IPO stock) and "cash" (to represent the refund of cash that the lottery losers get, which could be used to purchase the stock). It is worth noting that this model abstracts from a number of important features of our setting. Two important features are 1) in reality, the agent knows that the stock or cash were assigned randomly with some probability, and 2) the stock is itself a gamble whose value changes over time. We present a model with these additional features further on in this appendix.

In this model the decision process of lottery winners and losers is symmetric, just as in the Ericson and Fuster (2011) model of mugs and pens. The model will yield the same result whether the agent is randomly allocated the stock or cash, so we simply present and solve for the case in which the agent is randomly allotted the stock (i.e. the lottery winners).

We denote by $s$ the agent's expectation of what the stock will be worth in the future, and by the variable $c$ the value of the cash returned to lottery winners. To fix ideas, note that a standard expected-utility decision maker would choose to hold the stock if $s > c$, and sell the stock if $s < c$, regardless of whether they randomly win or lose the stock in the lottery.

In the model, once the lottery winner learns that he has won the lottery, but just prior to the stock listing, he makes a plan about whether or not to sell the stock after it lists on the exchange. The agent assumes that with probability $b$ he will be given the opportunity to trade the stock post-listing. This is an exogenously specified parameter in the Ericson-Fuster (2011) experiment, and we argue that in the Indian stock market setting in which investors know that they can trade the stock at very low explicit transactions costs, that $b = 1$. Under this assumption, we show that an endowment effect is not generated by this model, though it appears in our empirical setting.

Consider the case in which the lottery winner plans to trade the stock after it lists. For this plan to be an equilibrium, it must be the case that its expected utility is greater than the expected utility from planning to continue to hold the stock post-listing.

The expected utility from the plan to sell the stock is:

$$EU(\text{sell}|\text{plan to sell}) = bU(c|r) + (1-b)U(s|r) \tag{7}$$

In equation (7), $U(c|r)$ is the utility from selling the stock and keeping the cash. This utility has three pieces; the direct utility of consumption ($c$), the gain-loss utility from comparing the utility of holding cash to the reference point of holding the cash (this is simply 0), and the gain-loss utility from exchanging the stock for cash ($c - \lambda s$), compared to a reference point of holding the stock. This final piece captures the fact that the agent feels a loss from "losing" the stock while gaining cash, beyond any difference in expected value between the cash and the stock. In other words, this piece captures the pain of the agent giving up the endowed item (the stock).

Note that the gain-loss utility pieces are weighted by their probability of occurrence (with probability $b$, the agent can go ahead and exchange, so compares the outcome to the planned action, and with probability $1 - b$, is constrained from exchanging, and compares the outcome to the reference point of holding the stock), and the utility from holding the stock in the state of the world where the agent does not have the opportunity to trade is $U(s|r) = s + b(s - \lambda c)$. Plugging these into the equation above, we have:

$$EU(\text{sell}|\text{plan to sell}) = b(c + (1-b)(c - \lambda s)) + (1-b)(s + b(s - \lambda c))$$

The agent will follow through on his plan to trade if it delivers greater expected utility than a plan to hold the stock. The expected utility of holding the stock given the agent's plan to hold the stock is simply the consumption value of the stock $s$, because regardless of whether the agent is given the opportunity to trade, the agent will end up holding the stock (so the outcome and the expectations based reference point are always equal). Thus, the condition that determines whether the agent prefers the plan where he sells the stock to the plan to hold the stock is determined by:

$$\begin{aligned} EU(\text{sell}|\text{plan to sell}) &> EU(\text{hold}|\text{plan to hold}) \quad (8)\\ b(c+(1-b)(c-\lambda s))+(1-b)(s+b(s-\lambda c)) &> s\\ bc+(1-b)s+b(1-b)(c-\lambda s+s-\lambda c) &> s\\ c-s+(1-b)(1-\lambda)(c+s) &> 0 \quad (9)\end{aligned}$$

Equation (8) is identical to Proposition 1 of Ericson and Fuster (2011). When $b = 1$, the final equation simplifies to $c > s$, i.e., the agent's decision of whether to go through with the plan to sell the stock versus holding the stock is exactly the same as that of an expected utility decision maker. If the agent believes the stock is worth less than the refunded cash amount, he will sell the stock, and if he believes the stock is worth more than the refunded cash amount, he holds.

The intuition for the result is that when $b = 1$ the agent does not develop an expectations based reference point based on being forced to hold the stock; because this reference point is not developed, the agent does not feel an unusual added loss from selling the stock. If on the other hand, he was potentially forced to hold it, he would feel such an unusual added loss. Hence in this case, the decision to trade (or not trade) is determined by consumption values only. Since the problem is symmetric for lottery losers, the same condition will determine whether they will choose to buy the stock versus holding the cash.

In our field experiment, randomization should equalize the fraction of lottery winners and losers that believe that $s > c$. As a result, this model would predict that we should see equal fractions of the two groups holding the IPO stock. However, our data strongly rejects this suggestion, suggesting that the model of expectations based reference points studied in Ericson and Fuster (2011), which is able to explain their laboratory evidence on endowment effects, is unlikely to explain our findings.

A clear drawback of this model applied to our setting is that it models the stock as having a deterministic value like a consumption good. This is clearly unrealistic. We therefore turn to a more elaborate model which allows the stock to have stochastic payoffs.

## C.2 Sprenger (2015) Model

We now introduce an expectations based reference-dependent preferences model in which the agent views the stock as a lottery with probabilistic payoffs. We assume that the stock price can go up by $h$, with probability $q$ in the aftermarket, or down by $l$ with probability $1 - q$. The model takes as given that an agent has either won or lost the initial IPO allocation lottery, and simply studies the potential plans the agent could make about holding, selling, or buying the stock given these allocation lottery outcomes.

We begin with the lottery loser. The idea of the model is that because the lottery loser is endowed with cash, holding cash constitutes his expectations based reference point. The agent then has two possible plans to consider. The first plan is to simply not purchase the stock. The expected utility in this case is just the value of the cash returned in the lottery $c$; there is no gain-loss utility piece because the agent compares holding cash to the reference point of holding cash, yielding zero.

We next derive the condition necessary for the agent to not wish to deviate from their plan to hold the cash, i.e., the condition that makes the agent's plan to not hold the stock a personal equilibrium (PE).

The expected utility of deviating from the plan of not buying the stock is:

$$\begin{aligned}
EU(\text{buy stock}|\text{plan to not buy}) &= q(c+h+q(h)+(1-q)(h))+ \\
&\quad (1-q)(c-l+q\lambda(-l)+(1-q)\lambda(-l)) \\
&= q(c+h+h)+(1-q)(c-l-\lambda l) \\
&= q(c+2h)+(1-q)(c-(1+\lambda)l) \\
&= c+q2h-(1-q)(1+\lambda)l
\end{aligned}$$

The agent will choose not to deviate from the plan to not buy the stock if:

$$\begin{aligned}
EU(\text{plan to not buy}|\text{plan to not buy}) &> EU(\text{buy stock}|\text{plan to not buy}) \\
c &> c+q2h-(1-q)(1+\lambda)l \\
(1-q)(1+\lambda)l &> 2qh \\
\frac{1+\lambda}{2} &> \frac{qh}{(1-q)l} \qquad (10)
\end{aligned}$$

Note that when $\lambda = 1$ this condition simplifies to $0 > qh + (1-q)l$. That is, with no loss aversion, the agent prefers holding the cash only if the expected return on the stock is less than zero.

When $\lambda > 1$ there are two forces that affect whether the agent will stick to their plan of not buying the stock. First, as loss-aversion increases, this condition is more likely to hold. This is because buying the stock involves the possibility of taking on losses. Second, as the potential gains on the stock $qh$ increase relative to the potential losses $((1-q)l)$, the incentives to deviate from the plan and buy the stock increase. This is obvious – the expected returns with gains, and more importantly, the chance of experiencing large losses gets smaller. If we assume $h = l$, so that the expected return on the stock is only determined by $q$, and when $\lambda = 2$, we have that $q$ must be less than $\frac{3}{5}$ for not buying to be a PE.

Now consider the lottery winner. We assume that the lottery winner, who is endowed with the stock, has an expectations-based reference point of holding the stock. The lottery winner also faces two possible plans. The first of these is to hold the stock. The expected utility of this plan is:

$$\begin{aligned}
EU(\text{hold stock}|\text{plan to hold stock}) &= q(c+h+(1-q)(h+l))+(1-q)(c-l+q\lambda(-l-h)) \\
&= c+q(h+(1-q)(h+l))+(1-q)(-l+q\lambda(-l-h)) \\
&= c+qh+(1-q)(-l)+q(1-q)(1-\lambda)(h+l)
\end{aligned}$$

We can then calculate the expected utility of the lottery winner from deviating from this plan:

$$\begin{aligned}
EU(\text{hold cash}|\text{plan to hold stock}) &= q(c+q\lambda(-h)+(1-q)(l)) \\
&\quad +(1-q)(c+q\lambda(-h)+(1-q)(l)) \\
&= c+q\lambda(-h)+(1-q)l
\end{aligned}$$

The investor will follow through on his plan to hold the stock if:

$$EU(\text{hold stock}|\text{plan to hold stock}) > EU(\text{hold cash}|\text{plan to hold stock})$$

$$c+qh+(1-q)(-l)+q(1-q)(1-\lambda)(h+l) > c+q\lambda(-h)+(1-q)l$$

If we assume that $h=l$, this condition simplifies to $\sqrt{q}+q>1$, meaning that $q>0.4$.[18]

Combining the two no-deviation conditions, the expected return on the stock must fall in the following range for an investor to choose to stick with their plan of holding cash when they lose the lottery, and holding the stock when they win the lottery:

[18] We only need to consider the positive root of $\sqrt{q}$, since $0<q<1$, i.e., this condition can never hold for the negative root of $q$.

$$0.4 < q < 0.6$$

This result suggests that the endowment effect can be a PE (i.e, the lottery loser does not wish to deviate from their plan of holding cash, and the lottery winner does not wish to deviate from their plan to hold the stock), for a reasonable set of beliefs about the probability of the stock going up.

### C.2.1 Preferred Personal Equilibrium (PPE) Conditions

For the lottery loser, the PPE condition is:

$$\begin{aligned}
EU(\text{plan to not buy}|\text{plan to not buy}) &> EU(\text{buy stock}|\text{plan to buy}) && (11)\\
c &> c + qh + (1-q)(-l) + q(1-q)(1-\lambda)(h+l) \\
q(1-q)(\lambda-1)(h+l) &> qh + (1-q)(-l) && (12)
\end{aligned}$$

For the lottery winner, the PPE condition is:

$$\begin{aligned}
EU(\text{hold}|\text{plan to hold}) &> EU(\text{sell} \mid \text{plan to sell}) && (13)\\
c + qh + (1-q)(-l) + q(1-q)(1-\lambda)(h+l) &> c \\
qh + (1-q)(-l) &> q(1-q)(\lambda-1)(h+l) && (14)
\end{aligned}$$

Note that conditions (11) and (13) contradict each other. That is to say, agents holding the cash when they lose the lottery and holding the stock when they win the lottery cannot simultaneously constitute a PPE.

The intuition for this result is that in this model, planning to buy the stock and then following through on it (as a lottery loser) delivers exactly the same payoff as planning to hold the stock and following through on it (as a lottery winner). Similarly, planning not to buy the stock and following through on this plan as a lottery loser gives the same payoffs as planning to sell the stock and following through on this plan as a lottery winner. Given this symmetry of payoffs, and the (plausible) assumption that the randomized endowment does not change the investor's beliefs about future returns (i.e., $q$, $h$, $l$) or loss aversion ($\lambda$), the model cannot simultaneously generate losers who want to stay out of the stock and winners who want to stay in the stock.

Thus, while it is possible that we could observe this outcome because investors are playing their PEs, the fact that this behavior cannot be a PPE makes it unlikely that the model is able to explain the behavior that we observe in our empirical setting.

We now turn to a model which more realistically captures features of our empirical setting, including the fact that agents are randomly assigned the IPO stock in an initial lottery, following which they decide to either buy, sell, or hold the IPO stock.

## C.3 A Reference-Dependence Model of IPO Market Lotteries

To model the IPO setting in our empirical analysis, we include both the lottery which results in the agent being awarded the stock or not, as well as the (simplified) evolution of the stock price in the after-market – which we also model as a binary lottery.

The model begins with the agent applying to receive one share of a stock following the IPO allocation process described in the text. We then consider a set of possible plans and associated reference points, and solve for the PE in this setup. We identify parameter values for which we observe the endowment effect plan (where the agent holds the stock when they win, and does not purchase the stock if they lose) is a PE, and relate this back to our empirical tests.

- The first lottery that the agent faces is the IPO lottery. We model this as follows: with probability $p$ the agent wins the IPO lottery and receives one share of the stock, and with probability $1 - p$ the agent loses the lottery, and receives cash $c$ as a refund.

- The value of the stock that the winners receive at the point at which they win the lottery (and immediately before the stock is listed) is $s = c$. This realistically represents features of the lottery process, and captures the idea that lottery losers and winners start with the same amount of money before the stock is listed.

- The stock lists on the exchange at a value $s + x$, where $x$ is the listing gain. For simplicity, we assume $x > 0$, as 40 of the 54 IPOs in our empirical analysis had positive listing gains. Note this also amounts to assuming that agents expect a positive listing gain at the time of applying for the IPO.

- The stock trades freely after listing. Winners can choose to sell the stock at $s + x$ in the moment after listing. Losers can choose to buy the stock at $s + x$ in the moment after listing.

- After the stock lists, we also model the evolution of the stock price as a binary lottery. The stock price can either go up by an amount $h$ (with probability $q$) or go down by an amount $l$, with probability $1 - q$. This means that the final price of the stock is $s + x + h$ with probability $q$ and $s + x - l$ with probability $1 - q$. To fix intuition, we can think of these prices as those at the end of the day on which the stock lists.

- All decisions are made before the stock realizes its high or low value.

- We begin by assuming that $l < x$, i.e., the potential loss on the stock, post-listing, on the day that it lists, is modelled as smaller than the listing gain. This assumption will be important in determining whether certain outcomes are encoded as losses or gains (e.g., a lottery winner might not feel the pain of losing when the stock goes down in the after market because they are already sitting on a large listing gain.) We think of this assumption as implying that we are mainly concerned with the short-run, as in our sample of 54 IPOs only 8 had a larger loss from the listing price to the closing price on the first day than the listing gain (in the positive listing gain domain). Later, we analyze the long run case where $l > x$, i.e., the after-market losses could potentially be larger than the listing gain.

- We assume that the agents consume the value of the stock or cash held after the stock achieves its final price.

An agent in this model can have four potential plans which we summarize in Table C.3.1. In Plan 1, the agent sells the stock immediately after listing if she wins the lottery, and chooses not to buy the stock if she loses the lottery. In Plan 2, the agent chooses to hold the stock until the end of the first day if she wins the lottery, and to buy the stock immediately after listing if she loses the lottery. In Plan 3, the agent chooses to hold the stock until the end of the first day if she wins, but chooses not to purchase the stock if she loses the lottery. Finally, in Plan 4, the agent chooses to sell the stock immediately after listing if they win the lottery, but also to buy the stock after listing if they lose the lottery.

Table C.3.1: Plans of Action

| | Lottery Outcome: | |
|---|---|---|
| | Win Lottery | Lose Lottery |
| Plan 1 | Sell Stock at $s + x$ | Hold cash |
| Plan 2 | Hold Stock, realize $s + x + h$ or $s + x - l$ | Buy at $s + x$, realize $s + x + h$ or $s + x - l$ |
| Plan 3 | Hold Stock, realize $s + x + h$ or $s + x - l$ | Hold cash $s$ |
| Plan 4 | Sell Stock at $s + x$ | Buy at $s + x$, realize $s + x + h$ or $s + x - l$ |

To fix intuition, it is useful to think of Plan 3 as the "endowment effect plan." Under this plan, the agent chooses to make a *different* decision about the stock in the after-market based on whether they are endowed with the stock in the lottery. On the other hand, Plans 1 or 2 do not demonstrate endowment effects, because in both of those cases the agent plans to take the *same* decision on the stock in the after-market (in Plan 1 the agent does not want to hold the stock in the after-market regardless of winning or losing, and in Plan 2 the agent does wish to hold the stock in the after-market regardless of winning or losing). Plan 4 can be thought of as an "anti-endowment effect" plan, where being randomly assigned the stock in the lottery makes the agent *less* likely to want to hold it. To save space we do not formally analyze Plan 4 as it is not empirically relevant in our setting.

Table C.3.2 summarizes the utility consequences of pursuing Plans 1, 2, and 3. Each panel refers to a different plan, and the rows within each panel refer to the four possible states of the world that can occur. "Win" ("Lose") indicates winning (losing) the lottery, and the $\uparrow$ ($\downarrow$) symbol indicates the stock going up (down).

Table C.3.2: Consumption and Gain-Loss Utility Terms for Plans

| | | | Reference State | | | |
|---|---|---|---|---|---|---|
| Outcome State | Probability | Consumption | Win ↑ | Win ↓ | Lose ↑ | Lose ↓ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Plan 1 (Sell Stock if Win Lottery, Don't Buy Stock if Lose Lottery* | | | | | | |
| Win ↑ | $pq$ | $s+x$ | 0 | 0 | $(1-p)q(x)$ | $(1-p)(1-q)(x)$ |
| Win ↓ | $p(1-q)$ | $s+x$ | 0 | 0 | $(1-p)q(x)$ | $(1-p)(1-q)(x)$ |
| Lose ↑ | $(1-p)q$ | $s$ | $pq\lambda(-x)$ | $p(1-q)\lambda(-x)$ | 0 | 0 |
| Lose ↓ | $(1-p)(1-q)$ | $s$ | $pq\lambda(-x)$ | $p(1-q)\lambda(-x)$ | 0 | 0 |
| *Panel B: Plan 2 (Hold Stock if Win Lottery, Buy Stock if Lose Lottery* | | | | | | |
| Win ↑ | $pq$ | $s+x+h$ | 0 | $p(1-q)(h+l)$ | $(1-p)q(x)$ | $(1-p)(1-q)(x+h+l)$ |
| Win ↓ | $p(1-q)$ | $s+x-l$ | $pq\lambda(-l-h)$ | 0 | $(1-p)q(x-l-h)$ | $(1-p)(1-q)(x)$ |
| Lose ↑ | $(1-p)q$ | $s+h$ | $pq\lambda(-x)$ | $p(1-q)\lambda(-x+h+l)$ | 0 | $(1-p)(1-q)(h+l)$ |
| Lose ↓ | $(1-p)(1-q)$ | $s-l$ | $pq\lambda(-x-l-h)$ | $p(1-q)\lambda(-x)$ | $(1-p)q\lambda(-l-h)$ | 0 |
| *Panel C: Plan 3 (Hold Stock if Win Lottery, Don't Buy Stock if Lose Lottery* | | | | | | |
| Win ↑ | $pq$ | $s+x+h$ | 0 | $p(1-q)(h+l)$ | $(1-p)q(x+h)$ | $(1-p)(1-q)(x+h)$ |
| Win ↓ | $p(1-q)$ | $s+x-l$ | $pq\lambda(-l-h)$ | 0 | $(1-p)q(x-l)$ | $(1-p)(1-q)(x-l)$ |
| Lose ↑ | $(1-p)q$ | $s$ | $pq\lambda(-x-h)$ | $p(1-q)\lambda(-x+l)$ | 0 | 0 |
| Lose ↓ | $(1-p)(1-q)$ | $s$ | $pq\lambda(-x-h)$ | $p(1-q)\lambda(-x+l)$ | 0 | 0 |

The column labelled "Probability" gives the probability of the state occurring (e.g., the probability of winning the lottery and the stock going up is $pq$). The "Consumption" column shows the final consumption amount in each state of the world under this plan. For example, under Plan 1, the consumption amount if the agent wins the lottery is the value of the stock plus the listing gain, because the agent chooses to sell the stock right after it lists. We also see that under Plan 1, if the agent loses the lottery, the consumption value is just the value of the cash they get back ($c = s$).

Columns (3) - (6) show the gain loss utilities that the agent expects when she compares the current state (the row, $x$ in our notation above) to the reference state (the column, $r$ in our notation above). Note that these gain-loss utilities are weighted by the probability that the given reference state would be the outcome state. Intuitively, outcome states that are more likely to happen are more important as reference states compared to outcome states that are unlikely to happen. This weighting scheme follows exactly the weighting procedure of reference points followed in Koszegi-Rabin (2006), and subsequently utilized for stochastic referents by Sprenger (2015) among others.

For example, Column (3) of the first row gives the expected gain-loss utility when the realized state of the world is Win ↑ and the agent compares this outcome to the ex-ante expectation that the state of the world would be Win $\uparrow$; the value in the cell is $pq0 = 0$ because this state occurs with probability $pq$ and there is no gain-loss utility – the realized state of the world is equivalent to the the expectation based reference-point in that particular possible outcome. This logic also shows why the panels always have zeroes on the diagonals– because in those cells the agent is comparing the outcome state to the expectation of that realized state (which are identical), and therefore there is no gain-loss utility.

Column (4) of the first row also has a value of zero because here the agent is comparing winning the lottery and the stock going up to the expectation of the consumption outcome of winning the lottery and the stock going down, but in both of these states the consumption amount is the same (because the agent does not hold the stock in Plan 1).

In Plan 1 the non-zero gain-loss utility pieces only take two other possible values, $x$ or $\lambda(-x)$. When the agent wins the lottery and compares it to losing the lottery, the agent has a gain-loss utility of $x$ (the four upper right cells in Panel A); the agent feels particularly good about winning the lottery because she gets the listing gain she would not have received if she had lost the lottery. When the agent loses the lottery and compares it to winning the lottery, the gain loss utility is $\lambda(-x)$; the agent feels bad about losing the lottery because she compares to the listing gain she would have received had she won the lottery.

The remaining cells follow this logic and show the gain-loss terms. Two auxiliary assumptions are important to note in this context. First, in Plan 2, in the cell where the outcome state is Lose $\uparrow$, and the reference state is Win $\downarrow$ , we assume that $x > l + h$, i.e., the loss that the agent feels is because the loss of the listing gain is greater than the difference between the stock price in the up and down states. Second, we assume that the lottery losers do not consume the amount of the listing gain if they buy the stock in Plan 2.

The goal of our analysis is to determine the conditions under which an agent would prefer Plan 3 to *both* Plan 1 and Plan 2. Our analysis proceeds in three steps. First, we derive the condition that makes the agent want to follow through on Plan 3, as opposed to deviating to Plan 1, given that Plan 3 was her plan. Second, we derive the condition that makes the agent want to follow through on Plan 3, as opposed to deviating to Plan 2, given that Plan 3 was her plan. We then combine these two conditions to determine the parameter values that would make an agent choose to prefer following through on Plan 3 versus deviating to either Plan 1 or Plan 2. In other words (without considering Plan 4), we derive the parameter values under which Plan 3 constitutes a PE.

### C.3.1 Condition: No Deviation to Plan 1 Assuming Plan 3 is the Plan

We want to calculate $EU$[Follow Plan 3|Plan 3] $-$ $EU$[Follow Plan 1|Plan 3]. Table C.3.2 already summarizes $EU$[Follow Plan 3|Plan 3]. We compute $EU$[Follow Plan 1|Plan 3] below:

EU[Follow Plan 1 | Plan 3]

| | Probability | Consumption | Win ↑ | Win ↓ | Lose ↑ | Lose ↓ |
|---|---|---|---|---|---|---|
| Win ↑ | $pq$ | $s+x$ | $pq\lambda(-h)$ | $p(1-q)l$ | $(1-p)qx$ | $(1-p)(1-q)x$ |
| Win ↓ | $p(1-q)$ | $s+x$ | $pq\lambda(-h)$ | $p(1-q)l$ | $(1-p)qx$ | $(1-p)(1-q)x$ |
| Lose ↑ | $(1-p)q$ | $s$ | $pq\lambda(-x-h)$ | $p(1-q)\lambda(-x+l)$ | 0 | 0 |
| Lose ↓ | $(1-p)(1-q)$ | $s$ | $pq\lambda(-x-h)$ | $p(1-q)\lambda(-x+l)$ | 0 | 0 |

The table below shows $EU$[Follow Plan 3|Plan 3] $-$ $EU$[Follow Plan 1|Plan 3]:

| | Probability | Consumption | Win ↑ | Win ↓ | Lose ↑ | Lose ↓ |
|---|---|---|---|---|---|---|
| Win ↑ | $pq$ | $h$ | [a] $pq\lambda h$ | [b] $p(1-q)h$ | [e] $(1-p)qh$ | [f] $(1-p)(1-q)h$ |
| Win ↓ | $p(1-q)$ | $-l$ | [c] $pq\lambda(-l)$ | [d] $-p(1-q)l$ | [g] $(1-p)q(-l)$ | [h] $(1-p)(1-q)(-l)$ |
| Lose ↑ | $(1-p)q$ | 0 | 0 | 0 | 0 | 0 |
| Lose ↓ | $(1-p)(1-q)$ | 0 | 0 | 0 | 0 | 0 |

- The expected consumption difference is: $p[qh+(1-q)(-l)]$.
- Terms a,b,c and d sum to: $p^2[qh+(1-q)(-l)](q(\lambda-1)+1)$.
- Terms c,d,e and f sum to: $p(1-p)[qh+(1-q)(-l)]$.

Let $\bar{g} = qh + (1-q)(-l)$, the expected return to holding the stock in the aftermarket. Summing these three pieces we have the condition:

$$\begin{aligned}
EU[\text{Follow Plan 3}|\text{Plan 3}] - EU[\text{Follow Plan 1}|\text{Plan 3}] &> 0 \\
\bar{g}(p + p^2(q(\lambda-1)+1) + p(1-p)) &> 0 \\
\bar{g}p(1 + p(q(\lambda-1)+1) + (1-p)) &> 0 \\
p\bar{g}(2 + pq(\lambda-1)) &> 0
\end{aligned}$$

Given our assumption that the stock has a positive expected return $\bar{g} > 0$, this condition will always be true, i.e., given that the agent plans to pursue Plan 3, they will not wish to deviate to Plan 1, which involves "never holding" or "always selling" the positive expected return stock.

### C.3.2 Condition: No Deviation to Plan 2 Assuming Plan 3 is the Plan

We want to calculate $EU$[Follow Plan 3|Plan 3] $-$ $EU$[Follow Plan 2|Plan 3]. Table C.3.2 already summarizes $EU$[Follow Plan 3|Plan 3]. We compute $EU$[Follow Plan 2|Plan 3] below:

EU[Follow Plan 2| Plan 3]

| | Probability | Consumption | Win ↑ | Win ↓ | Lose ↑ | Lose ↓ |
|---|---|---|---|---|---|---|
| Win ↑ | $pq$ | $s+x+h$ | 0 | $p(1-q)(h+l)$ | $(1-p)q(x+h)$ | $(1-p)(1-q)(x+h)$ |
| Win ↓ | $p(1-q)$ | $s+x-l$ | $pq\lambda(-l-h)$ | 0 | $(1-p)q(x-l)$ | $(1-p)(1-q)(x-l)$ |
| Lose ↑ | $(1-p)q$ | $s+h$ | $pq\lambda(-x)$ | $p(1-q)\lambda(-x+h+l)$ | $(1-p)qh$ | $(1-p)(1-q)h$ |
| Lose ↓ | $(1-p)(1-q)$ | $s-l$ | $pq\lambda(-l-x-h)$ | $p(1-q)\lambda(-x)$ | $(1-p)q\lambda(-l)$ | $(1-p)(1-q)\lambda(-l)$ |

The table below shows $EU$[Follow Plan 3|Plan 3] $-$ $EU$[Follow Plan 2|Plan 3]:

| | Probability | Consumption | Win $\uparrow$ | Win $\downarrow$ | Lose $\uparrow$ | Lose $\downarrow$ |
|---|---|---|---|---|---|---|
| Win $\uparrow$ | $pq$ | 0 | 0 | 0 | 0 | 0 |
| Win $\downarrow$ | $p(1-q)$ | 0 | 0 | 0 | 0 | 0 |
| Lose $\uparrow$ | $(1-p)q$ | $-h$ | $^{a}pq\lambda(-h)$ | $^{b}p(1-q)\lambda(-h)$ | $^{e}-(1-p)qh$ | $^{f}-(1-p)(1-q)h$ |
| Lose $\downarrow$ | $(1-p)(1-q)$ | $l$ | $^{c}pq\lambda l$ | $^{d}p(1-q)\lambda l$ | $^{g}(1-p)q\lambda l$ | $^{h}(1-p)(1-q)\lambda l$ |

- The expected consumption difference is: $(1-p)[q(-h)+(1-q)l] = (1-p)(-\bar{g})$.
- Terms a,b,c and d sum to: $(pq\lambda + p(1-q)\lambda)(1-p)(-\bar{g})$.
- Terms e,f,g and h sum to: $(1-p)^2(-\bar{g}) + (1-p)^2(1-q)(1-\lambda)l$.

Summing these three pieces we have the condition:

$$
\begin{aligned}
(1-p)\left((1+p\lambda+(1-p))(-\bar{g}) - (1-p)(1-q)(1-\lambda)l\right) > 0 \\
(1+p\lambda+(1-p))(-\bar{g}) &> (1-p)(1-q)(1-\lambda)l \\
(1+p\lambda+(1-p))q(-h) &> (1-q)[(1-p)(1-\lambda) \\
&\qquad - 1 - p\lambda - 1 + p]l \\
(1+p\lambda+(1-p))q(-h) &> (1-q)(-\lambda-1)l \\
(1+p\lambda+(1-p))q(-h) &> (1-q)(1+\lambda)(-l)
\end{aligned}
$$

Note that with no loss-aversion ($\lambda = 1$), the final equation simplifies to $0 > \bar{g}$, which says that with no loss-aversion, the agent does not deviate from Plan 3 to Plan 2 only in the case where the expected return on the stock is less than zero. However, if that were true, the agent would deviate from Plan 3 to Plan 1 (as shown above). Taken together, if the agent has no loss-aversion, Plan 3 can never be a PE.

### C.3.3 Understanding Our No-Deviation Conditions

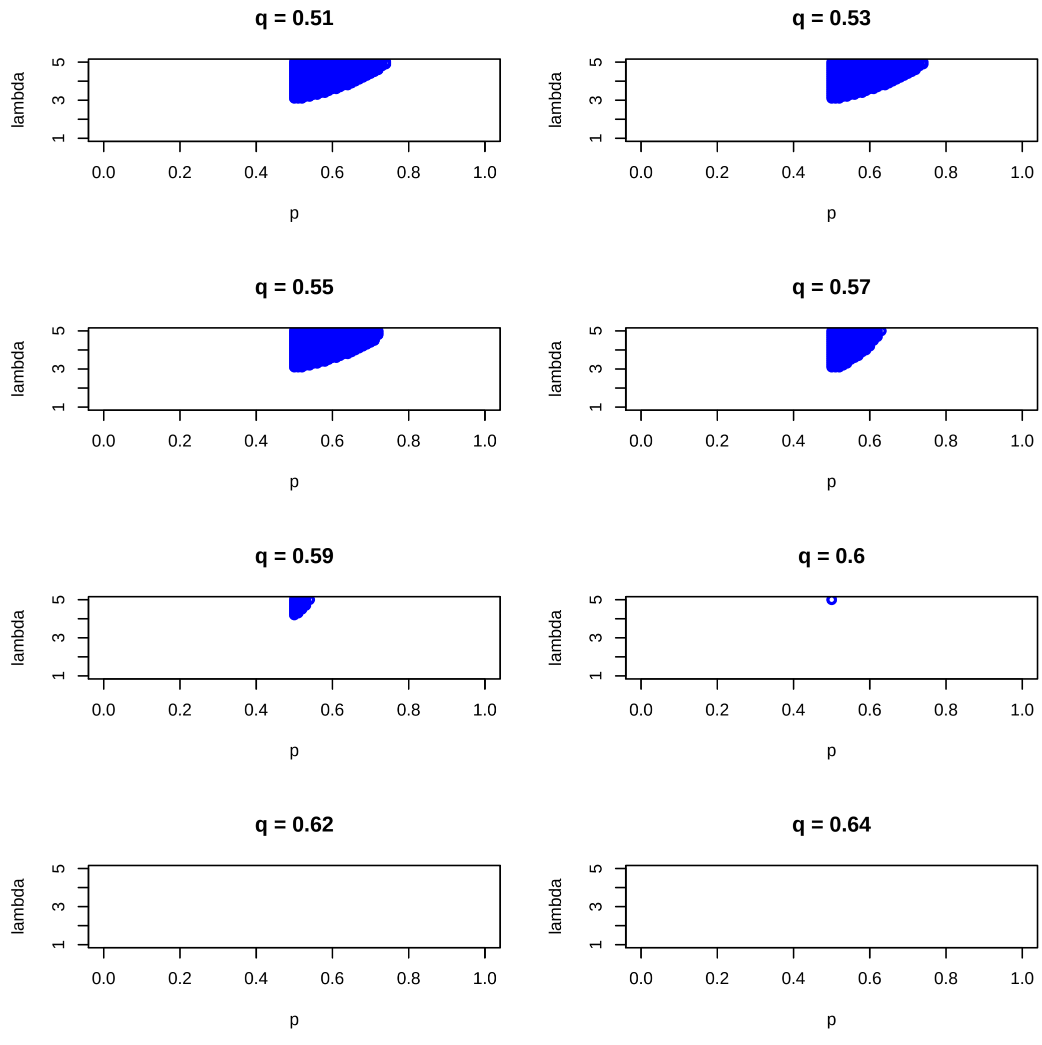
We know that $\overline{g} > 0$ from the no-deviation condition for Plan 3 to Plan 1, which implies that $\frac{qh}{(1-q)l} > 1$. From the no-deviation condition from Plan 3 to Plan 2 we have $\frac{qh}{(1-q)l} < \frac{1+\lambda}{2+p(\lambda-1)}$. So for the agent to neither prefer to deviate to Plan 1 or Plan 2 we need the following inequalities to hold simultaneously:

$$1 < \frac{qh}{(1-q)l} < \frac{1+\lambda}{2+p(\lambda-1)} \tag{15}$$

We can interpret this condition as giving a range of what the expected return on the stock in the after-market has to be to make the agent to choose to follow through on Plan 3 versus deviating to the other plans. The expected return has to be bounded because if it is too low, the agent never wants to hold the stock, and would just prefer Plan 1. And if the return is too high, the agent will deviate from Plan 3 to Plan 2, where they hold the stock regardless of whether they win or lose the lottery.

For relating this condition to our data, the most interesting feature of this result is that as $p$ approaches 1 from below, the term $\frac{1+\lambda}{2+p(\lambda-1)}$approaches 1 as well (from above). This means that for $p \approx 1$ there will be a very small window that the term $\frac{qh}{(1-q)l}$ must fall in to for this model to generate an endowment effect. For example, if $\lambda = 2$ and $p = 0.99$ we have that $1 < \frac{qh}{(1-q)l} < 1.003$. This implies that the condition simplifies to: $0.5 < \frac{qh}{(1-q)l} < 0.5007$. This means that when $p$ is close to 1, Plan 3 as a PE is a knife-edge case, where only agents who expect the stock to have an expected return of very close to zero will choose not to deviate to Plan 1 or Plan 3. Figure C.3.1 plots of the possible combinations of $p$ and $\lambda$ that can satisfy both of our no-deviation conditions (condition (15)), and therefore deliver an endowment effect in this model. In these plots we assume $h = l$, i.e. the only determinant of the expected return on the stock is $q$. Note that if $q < 0.5$ we can never get an endowment effect, because then the agent always wants to deviate to Plan 1 from Plan 3. We therefore only plot the combinations of $p$ and $\lambda$ that deliver an endowment effect for $q \geq 0.5$. Focusing

Figure C.3.1: No Deviation Conditions



on values of $p$ greater than 0.8, the figure shows $q$ has to be very close to 0.5 for this model to generate an endowment effect.

The intuition for this result is that when $p$ gets close to 1 in this model the comparisons agents make across winning and losing the lottery become less and less important, because it is unlikely that they will lose the lottery. As the comparison across winning and losing gets less important, decision making depends more and more on the simple expected return of the stock, which pushes agents towards either Plan 1 if the expected return is low, or Plan 2 if the expected return is high.

Empirically, what this says is that when $p$ gets close to 1 the only people who should prefer Plan 3 are those who believe the probability of the stock going up or down is in a very narrow range. Assuming that the distribution of expected returns on the IPO stock is not degenerate, we should find a vanishingly small endowment effect as the probability of winning the lottery approaches 1. Looking at our empirical estimates of how the endowment effect varies with the probability of winning a given lottery (Table 6), when $p$ goes form zero to one we find the endowment effect only goes down from 0.73 to 0.59. While the fact that the estimated endowment effect gets smaller as the probability of winning is consistent with this model, it seems implausible that 59 percent of lottery applicants would believe that the return on the IPO stock is in a very narrow range around zero. For example, these beliefs would be very different from the observed empirical distribution of IPO returns over our sample period where only 1.8 percent of IPOs had returns between 0 and 1 percent over six months.

We have also gone further and derived the conditions necessary for Plan 3 (the endowment effect plan) to be a PPE, i.e. the (preferred) personal equilibrium with the highest expected utility. We find that the ranges of $p$ and $\lambda$ required to make Plan 3 a PPE are substantially smaller than those that deliver Plan 3 as a preferred equilibrium. In particular, Plan 3 is not a PPE even in the case where $p$ is close to 1 and $q$ is exactly equal to 0.5. These results further support the idea that Plan 3 is very unlikely to be optimal for lotteries where $p$ is close to 1, which contradicts our empirical results. As noted in Koszegi and Rabin (2006), the preferred personal equilibrium must naturally also be a personal equilibrium, otherwise the agent would have an incentive to deviate from their equilibrium choices, so for brevity we do not report those results here (available upon request).

### C.3.4 The Case of $l > x$

We now consider the case in which $l > x$, i.e., the potential loss on the stock, post-listing, on the day that it lists, is modelled as *larger* than the listing gain. We think of this assumption as describing the long run case in which the after-market losses from holding the stock could potentially be larger than the listing gain.

An agent in this model has the same four potential plans summarized in Table C.3.1. As before, Plan 3 is the "endowment effect plan." Once again, we omit consideration of Plan 4, the "anti-endowment effect" plan as it is not empirically relevant in our setting.

**No-Deviation Condition from Plan 3 to Plan 1** ($l > x$) We wish to calculate $EU$[Follow Plan 3|Plan 3] $-$ $EU$[Follow Plan 1|Plan 3].

$EU$[Follow Plan 3|Plan 3] can be represented in tabular form as:

EU[Follow Plan 3 | Plan 3]

| | Probability | Consumption | Win ↑ | Win ↓ | Lose ↑ | Lose ↓ |
|---|---|---|---|---|---|---|
| Win ↑ | $pq$ | $s+x+h$ | 0 | $p(1-q)(h+l)$ | $(1-p)q(x+h)$ | $(1-p)(1-q)(x+h)$ |
| Win ↓ | $p(1-q)$ | $s+x-l$ | $pq\lambda(-l-h)$ | 0 | $(1-p)q\lambda(x-l)$ | $(1-p)(1-q)\lambda(x-l)$ |
| Lose ↑ | $(1-p)q$ | $s$ | $pq\lambda(-x-h)$ | $p(1-q)(-x+l)$ | 0 | 0 |
| Lose ↓ | $(1-p)(1-q)$ | $s$ | $pq\lambda(-x-h)$ | $p(1-q)(-x+l)$ | 0 | 0 |

$EU$[Follow Plan 1|Plan 3]:

EU[Follow Plan 1 | Plan 3]

| | Probability | Consumption | Win ↑ | Win ↓ | Lose ↑ | Lose ↓ |
|---|---|---|---|---|---|---|
| Win ↑ | $pq$ | $s+x$ | $pq\lambda(-h)$ | $p(1-q)l$ | $(1-p)qx$ | $(1-p)(1-q)x$ |
| Win ↓ | $p(1-q)$ | $s+x$ | $pq\lambda(-h)$ | $p(1-q)l$ | $(1-p)qx$ | $(1-p)(1-q)x$ |
| Lose ↑ | $(1-p)q$ | $s$ | $pq\lambda(-x-h)$ | $p(1-q)(-x+l)$ | 0 | 0 |
| Lose ↓ | $(1-p)(1-q)$ | $s$ | $pq\lambda(-x-h)$ | $p(1-q)(-x+l)$ | 0 | 0 |

And finally, $EU$[Follow Plan 3|Plan 3] $-$ $EU$[Follow Plan 1|Plan 3]:

| | Probability | Consumption | Win ↑ | Win ↓ | Lose ↑ | Lose ↓ |
|---|---|---|---|---|---|---|
| Win ↑ | $pq$ | $h$ | $^{a}pq\lambda h$ | $^{b}p(1-q)h$ | $^{e}(1-p)qh$ | $^{f}(1-p)(1-q)h$ |
| Win ↓ | $p(1-q)$ | $-l$ | $^{c}pq\lambda(-l)$ | $^{d}-p(1-q)l$ | $^{g}(1-p)q((\lambda-1)x-\lambda l)$ | $^{h}(1-p)(1-q)((\lambda-1)x-\lambda l)$ |
| Lose ↑ | $(1-p)q$ | 0 | 0 | 0 | 0 | 0 |
| Lose ↓ | $(1-p)(1-q)$ | 0 | 0 | 0 | 0 | 0 |

- The expected consumption difference is: $p[qh+(1-q)(-l)]$.
- Terms a,b,c and d sum to: $p^2[qh+(1-q)(-l)](q(_{\lambda-1})+1)$
- Terms c,d,e and f sum to: $p(1-p)[\bar{g}+(1-q)(\lambda-1)(x-l)]$

Let $\bar{g}=qh+(1-q)(-l)$. Summing these three pieces we have the condition:

$$EU[\text{Follow Plan 3}|\text{Plan 3}] - EU[\text{Follow Plan 1}|\text{Plan 3}] > 0$$
$$\bar{g}(p+p^2(q(\lambda-1)+1)+p(1-p))+p(1-p)(1-q)(\lambda-1)(x-l) > 0$$
$$\bar{g}(2+pq(\lambda-1))-(1-p)(1-q)(\lambda-1)(l-x) > 0$$
$$\bar{g} > \frac{(1-p)(1-q)(\lambda-1)(l-x)}{2+pq(\lambda-1)}$$

With no loss-aversion ($\lambda = 1$),this condition simplifies to $\bar{g} > 0$; the agent will not deviate to Plan 1 as long as the expected return on the stock is greater than zero.

**No-deviation Condition from Plan 3 to Plan 2 ($l > x$)** We want to calculate $EU$[Follow Plan 3|Plan 3] − $EU$[Follow Plan 2|Plan 3]. We already have the first piece in table form, now we need to calculate the second piece in table form.

EU[Follow Plan 2| Plan 3]

| | Probability | Consumption | Win ↑ | Win ↓ | Lose ↑ | Lose ↓ |
|---|---|---|---|---|---|---|
| Win ↑ | $pq$ | $s+x+h$ | 0 | $p(1-q)(h+l)$ | $(1-p)q(x+h)$ | $(1-p)(1-q)(x+h)$ |
| Win ↓ | $p(1-q)$ | $s+x-l$ | $pq\lambda(-l-h)$ | 0 | $(1-p)q\lambda(x-l)$ | $(1-p)(1-q)\lambda(x-l)$ |
| Lose ↑ | $(1-p)q$ | $s+h$ | $pq\lambda(-x)$ | $p(1-q)(-x+h+l)$ | $(1-p)qh$ | $(1-p)(1-q)h$ |
| Lose ↓ | $(1-p)(1-q)$ | $s-l$ | $pq\lambda(-l-x-h)$ | $p(1-q)\lambda(-x)$ | $(1-p)q\lambda(-l)$ | $(1-p)(1-q)\lambda(-l)$ |

The next table gives $EU$[Follow Plan 3|Plan 3] − $EU$[Follow Plan 3|Plan 2].

| | Probability | Consumption | Win ↑ | Win ↓ | Lose ↑ | Lose ↓ |
|---|---|---|---|---|---|---|
| Win ↑ | $pq$ | 0 | 0 | 0 | 0 | 0 |
| Win ↓ | $p(1-q)$ | 0 | 0 | 0 | 0 | 0 |
| Lose ↑ | $(1-p)q$ | $-h$ | [a] $pq\lambda(-h)$ | [b] $p(1-q)(-h)$ | [e] $-(1-p)qh$ | [f] $-(1-p)(1-q)h$ |
| Lose ↓ | $(1-p)(1-q)$ | $l$ | [c] $pq\lambda l$ | [d] $p(1-q)(-x+(1-\lambda)l)$ | [g] $(1-p)q\lambda l$ | [h] $(1-p)(1-q)\lambda l$ |

- The expected consumption difference is: $(1-p)[q(-h)+(1-q)l] = (1-p)(-\bar{g})$.
- Terms a,b,c and d sum to: $(1-p)p[(-\bar{g})((\lambda-1)q+1)-(1-q)^2(x+\lambda)l]$
- Terms e,f,g and h sum to: $(1-p)^2(-\bar{g})+(1-p)^2(1-q)(1-\lambda)l$

Summing these three pieces we have the condition:

$$-\bar{g}+p[(\bar{g})((\lambda-1)q+1)-(1-q)^2(x+\lambda)l]+(1-p)(-\bar{g})+(1-p)(1-q)(1-\lambda)l>0$$

$$(-\bar{g})(2-p)+(-\bar{g})p((\lambda-1)q+1))+p(1-q)^2(x+\lambda)(-l)+(1-p)(1-q)(\lambda-1)(-l)>0$$

$$\frac{(1-q)(-l)[p(1-q)(x+\lambda)+(1-p)(\lambda-1)]}{2+pq(\lambda-1)}>\bar{g}$$

Note that with no loss-aversion ($\lambda = 1$) the last equation simplifies to $0 > \bar{g}$, which says that with no loss-aversion the agent chooses to not deviate only in the case where the expected return on the stock is less than zero. However, in that case, they would deviate from Plan 3 to Plan 1 (as shown above), so with no loss-aversion Plan 3 can never be a PE.

**No-Deviation Conditions Summary ($l > x$)** Combining the no-deviation conditions that guarantee that the investor will choose to follow through on Plan 3 instead of deviating to Plan 1 or Plan 3, we have:

$$\frac{(1-p)(1-q)(\lambda-1)(l-x)}{2+pq(\lambda-1)}<\bar{g}<\frac{(1-q)(-l)[p(1-q)(x+\lambda)+(1-p)(\lambda-1)]}{2+pq(\lambda-1)}$$

Given that $l > x$ in this case, we know that the left-hand-side of this inequality will be greater than zero. The right-hand-side of this inequality will always be less than zero. This implies that there is no possible value of $\bar{g}$ that will be able to satisfy both of these no-deviation conditions simultaneously.

## C.4 Brief Discussion of Reference-Dependence Models

Overall, the conclusions from our analysis of the various reference dependence models is that it is difficult to use these models to justify our empirical results. The parameter values required for the endowment effect to appear as a PE or PPE in our setting are quite restrictive, and the comparative statics predicted by the models in this class do not seem to match up closely to the observations in our field setting.

We now turn to examining other models that have been used in the literature to explain the endowment effect. We begin by describing the model of Weaver and Frederick (2012) in the next section.

# D Issue Price as the Reference Price (Weaver-Frederick Model)

The main idea of the framework of Frederick and Weaver (2012) applied to our setting is that investors may see trading at the market price of the stock as a bad deal because it seems worse to them than transacting at the issue price. This is a behavioral alternative to comparing their private valuation to the market price when deciding to trade, which would characterize the decision of a standard expected utility maximizing investor.

This model formalizes the intuition that some lottery losers, despite believing that the stock is worth more than the listing price $(s + x)$, may nevertheless not purchase it because they feel transacting at that price is a "bad deal" relative to the issue price $s$. This channel operates despite the fact that as a lottery loser, they never had the opportunity to purchase the stock at the issue price.

The basic setup of the model inherits the features and notation of the models solved earlier in the appendix, with the following additions: Investor $i$ has valuation $v_i$ for the stock in the moment after it lists. A rational lottery winner would hold the stock if their private valuation $v_i > s + x$, and sell otherwise, and a rational lottery loser would buy the stock if their $v_i > s + x$, and not buy otherwise. However, when the agent in this model thinks about trading the stock, he compares the market price to a distorted valuation which is a function of $v_i$ *and the issue price* $s$ (the reference price in our setting). The distortion works as follows: If trading at $v_i$ would create a loss relative to $s$, then the agent's distorted valuation is lower than their true valuation. In particular, Weaver and Frederick model the distorted valuation as a linear combination of the true valuation and the reference (issue) price:

$$v_i^b = \alpha_L s + (1 - \alpha_L) v_i,$$

where we use $v_i^b$ to denote the distorted valuation of the prospective *buyer*, $\alpha_L$ is a distortion parameter that is the weight the agent places on $s$ when determining the distorted valuation.

Consider for example an IPO with issue price $s = 100$ and listing price $s + x = 120$. Consider a lottery loser whose true valuation of the stock $v_i = 130$. If this investor was a standard expected utility decision maker, she would be willing to buy the IPO stock at any price up to 130. However, in this model, buying at 130 would be perceived as a loss relative to $s = 100$. In the model, this would create a distorted valuation which is lower than $v_i$. Say the agent has $\alpha_L = 0.4$, then the investor's distorted valuation would be $v_i^b = (0.4)100 + (1 - 0.4)130 = 118$, and the investor would choose not to purchase the IPO at the listing price of 120.

Now consider the case in which the agent has a private valuation $v_i$ such that transacting creates a *gain* relative to the issue price. In this case, the agent simply uses $v_i$ when making decisions, i.e., there is no distortion. In the example above, a lottery loser with $v_i = 90$ will see buying as delivering a gain since $s = 100$, and therefore no distortion is applied to their valuation.[19]

Taken together, for lottery losers (prospective buyers) the distorted valuation function takes the following form:

[19] Weaver and Frederick (2012) present a generalized model in their appendix where transactions at valuations that produce gains relative to the issue price also have a distortion parameter $\alpha_G$.They note that all of their results go through as long as $\alpha_L > \alpha_G$, which is true for our results as well given that ours is an application of their basic model.

$$
\begin{aligned}
v_i^b &= \alpha_L s + (1-\alpha_L)v_i \text{ if } v_i > s \\
v_i^b &= v_i \text{ if } v_i \leq s
\end{aligned}
$$

Analogously, a lottery winner's (prospective sellers') distorted valuation function takes the form:

$$
\begin{aligned}
v_i^s &= v_i \text{ if } v_i > s \\
v_i^s &= \alpha_L s + (1-\alpha_L)v_i \text{ if } v_i \leq s
\end{aligned}
$$

If the lottery winner values the stock more than the issue price, then they see selling at their valuation as a gain, and there is no distortion. However, if they value the stock less than the issue price, then they see view selling at their valuation as a loss relative to the issue price, and therefore have a distorted valuation. In particular, winners who value the stock less than the issue price will have a distorted valuation that is higher than their true valuation.

### D.1 Issue Price as Reference Price, Positive Listing Gain ($x > 0$)

We begin by analyzing the model in the case in which there is a positive listing gain, i.e. $x > 0$. We first consider the case where an investor's valuation is greater than the listing price, $v_i > s + x$. For a lottery winner, $v_i^s = v_i > s$, so the investor always wishes to hold the stock as their valuation is undistorted in this case. On the other hand, a lottery loser will purchase the stock after it lists if

$$
v_i^b = \alpha_L s + (1-\alpha_L)v_i > s + x, \tag{16}
$$

since their valuation is distorted on the buy side (as $v_i > s$).

Re-arranging equation (16), lottery losers will only hold the stock if $v_i > \frac{s+x}{1-\alpha_L}$. As $x > 0$ and $\alpha_L \in (0, 1]$, the right hand side is larger than $s + x$. Put differently, lottery losers require a higher valuation before they are interesting in purchasing the stock, compared to the valuation that lottery winners need to hold the stock, creating a wedge between the behavior of winners and losers.

The intuition for this result is that losers' valuations are anchored by the issue price, and this anchoring reduces their willingness to pay for the stock even if their true valuation of the stock is higher than the listing price. This difference in valuations implies there will be some lottery participants who would choose to hold the stock if they win the lottery, but would not choose to buy the stock if they lost the lottery – the endowment effect.

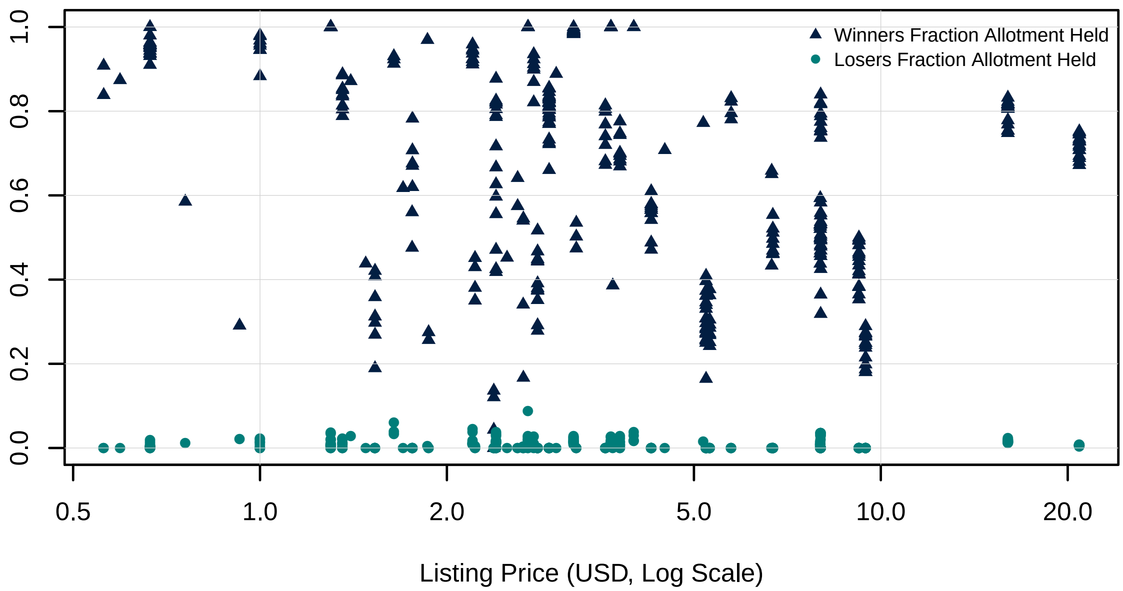
Next, consider the case where an investor's valuation is between the issue price and the listing price, $s < v_i < s+x$. In this case, all lottery winners choose to sell the stock because they value it less than the market price, and there is no distortion in their valuation because selling at these valuations constitutes a gain relative to the issue price. And, no lottery losers will choose to buy the stock because their distorted valuation ($v_i^b = \alpha_L s + (1 - \alpha_L)v_i$) is less than their true valuation ($v_i$), which is in turn less than the market price ($s + x$). So, in this case both winners and losers will both choose not to hold the stock, meaning that the model cannot generate an endowment effect.

Finally, consider the case where the agent's valuation of the stock is less than the issue price ($v_i < s$). In this case, lottery losers will see buying at their valuation as a gain relative to the issue price, resulting in no distortion to their true valuation $v_i^b = v_i$. Given that $v_i < s < s + x$, these lottery losers never purchase the stock after it lists. Lottery winners, however, see transacting at their valuation as a loss relative to the issue price, so $v_i^s = \alpha_L s + (1 - \alpha_L)v_i > v_i$, i.e., their distorted valuation is greater than their true valuation because of their attachment to the reference price. Nonetheless, this distorted valuation is still always less than the listing price $s + x$ (because $x > 0$) and therefore all lottery winners will choose to sell. Thus, for lottery applicants with valuations lower than the listing price neither lottery winners nor losers will want to hold the stock after it lists, and once again, there is no endowment effect in this group.

Overall, if there is a positive listing gain, the model predicts that only those "optimistic" investors with valuations greater than the market price ($v_i > s + x$) exhibit an endowment effect. In particular, the size of the endowment effect will be larger as the wedge between the cutoff valuations of lottery losers and lottery winners increases. Subtracting the lottery winners cutoff valuation from the lottery losers' valuation we get that the size of this wedge is $\frac{\alpha_L(s+x)}{1-\alpha_L}$. This expression shows that the wedge is increasing in the extent of loss aversion $\alpha_L$.[20] However, as we do not observe individual investors degree of loss aversion directly, this prediction cannot be tested.

The expression also shows that the endowment effect is increasing in $s + x$, and in particular, in $x$, the size of the listing gain. As the listing gain increases, lottery losers' maximum buying prices get increasingly distorted by the fact that the issue price is more and more below the transaction price after listing. We can inspect whether this comparative static finds support in the data, i.e., if this model is to explain our evidence, we should see smaller endowment effects for IPOs with small listing gains, and larger endowment effects for IPOs with large listing gains. In Figures 1a and 1b, however, we find little relationship between the size of the listing gains and the endowment effect. We also plot the endowment effect against the size of the total listing price $s + x$ in the figure below, and no relationship between the two is apparent as predicted by the model.

[20]Note that when $\alpha_L = 0$ there is no endowment effect; loss aversion is necessary in this model to generate an endowment effect.




More importantly, given that this model generates the endowment effect through a distorted valuation for lottery losers, we should see lottery losers being increasingly willing to buy the stock for small listing gains and increasingly unwilling to buy the stock for large listing gains. However, the first order fact here is that lottery losers do not increase their propensity to buy the stock when listing gains are low. In the paper, when we control for a host of IPO level covariates (which likely control for at least some of the underlying variation in loss aversion of investors across IPOs), we find a very small positive/negative relationship between the listing return and the size of the endowment effect.

## D.2 Issue Price as Reference Price, Negative Listing Gain ($x < 0$)

We also consider the case where the listing gain is negative. We begin with investors whose valuations are less than the listing price ($v_i < s + x < s$). The lottery losers in this group view buying at their valuation as a gain, so $v_i^b = v_i$, and they will not purchase the stock because $v_i^b < s + x$. Lottery winners view selling at their valuation as a loss relative to the issue price, and therefore have distorted valuations $v_i^s = \alpha_L s + (1 - \alpha_L)v_i$. They hold the stock if $\alpha_L s + (1-\alpha_L)v_i > s + x$, which simplifies to $v_i > s + \frac{x}{1-\alpha_L}$. Given that $x < 0$,there is a set of lottery winners with valuations that satisfy $(s + \frac{x}{1-\alpha_L} < v_i < s + x)$ that choose to hold the stock. Once again, in this case, a "pessimistic" group of investors can generate an endowment effect when the listing gain is negative.

Consider the set of investors with valuations in the range $s+x < v_i < s$. The lottery losers in this group view buying at their valuation as a gain, so their distorted valuation is equal to their true valuation ($v_i^b = v_i$). All of these lottery losers will purchase the stock. Lottery winners view selling at their valuation as a loss relative to the issue price, and therefore, as in the case above, their valuations will be distorted upwards towards the issue price. Therefore, all of these lottery winners will also choose to hold the stock, and this set of investors does not produce an endowment effect as winners and losers both choose to hold the stock.

Finally, consider investors with valuations $s+x < s < v_i$. Lottery losers will see buying at their valuation as a loss, and will have distorted valuations $v_i^b = \alpha_L s + (1-\alpha_L)v_i$. However, these distorted valuations are still always greater than $s + x$, so they always purchase the stock. Lottery winners see selling at their valuation as a gain relative to the issue price, and so there is no distortion and they all choose to hold the stock. There is no endowment effect in this case.

Similar to the case of the positive listing gain, we have here that the size of the endowment effect is a function of the listing gain and the loss-aversion weighting parameter. As $x$ approaches zero from below, the size of the endowment effect should also approach zero. We only have two IPOs in our dataset that experienced negative listing returns, so we have limited ability to test this. Nevertheless, Figure 1a and 1b show that for the two IPOs that had relatively small negative listing returns of -5 and -3 percent respectively, lottery winners are approximately 45 and 65 percent more likely to hold the stock than lottery losers. This evidence, along with the evidence regarding positive return IPOs, again suggest that a model where the endowment effect is driven by investors behaving as if the issue price is a reference price is unable to completely explain our empirical results. Note also that this model relies on optimistic investors to drive the endowment effect when listing gains are positive, and pessimistic investors to drive the effect when listing gains are negative – this potentially also generates additional testable implications in future studies which may be able to identify optimistic and pessimistic investors.

Overall, while the model is able to generate an endowment effect, its correspondence with our empirical results make it unlikely to be the principal driver of the endowment effect in our setting. We next turn to the realization utility model of Shefrin and Statman (1985) and Barberis and Xiong (2012).

# E Realization Utility Model With Loss Aversion

In this model the investor gets utility from *realized* gains and losses, i.e. utility from trading in the stock market comes not from future consumption or wealth levels, but instead in the instant in which a stock is sold. We are motivated to study this model because realization utility is the leading theoretical explanation of the disposition effect (Shefrin and Statman (1985), Barberis (2012)), and we observe strong disposition-effect type behavior amongst lottery winners in how they trade the IPO stock in the after-market, i.e., winners are more likely to sell IPO stocks that have gained versus lost value, see Figure 1c and 1d.[21] Our primary question of interest is whether a realization utility model, applied to our setting, can also explain the fact that lottery winners are so much more likely to hold the IPO stock than lottery losers (i.e. the endowment effect).

In this model, lottery losers choose whether to buy based on comparing the utility from doing nothing when the stock lists (which gives realization utility of zero), or buying the stock and getting realization utility in the future when they eventually sell it. Lottery losers will buy the stock if $qh + (1 - q)\lambda(-l)] > 0$. Note that the model requires loss aversion

[21] There is an active debate in the literature regarding to what extent the realization utility model can explain the disposition effect, and other features of the relationship between past returns and individual investor selling behavior. Ben-David and Hirshleifer (2012) discuss to what extent realization utility can explain the relationship between past returns and selling behavior; the basic empirical pattern of investors selling more as returns increase is similar in our setting to theirs.

parameter $\lambda$ applied to losses. Note also that this condition does not depend on the listing gain, as the listing gain is irrelevant to the lottery loser's realization utility from buying (or not buying) the IPO stock.

We next describe the conditions that determine whether the lottery winner will hold the stock. First consider the case in which the listing gain is negative ($x < 0$), and greater in magnitude than the upside on the stock in the aftermarket ($x + h < 0$). The lottery winner will hold the stock if:

$$\begin{aligned} q\lambda(x+h) + (1-q)\lambda(x-l) &> \lambda x \\ qh + (1-q)(-l) &> 0 \end{aligned}$$

Next, consider the case in which the listing gain is negative, but ($x + h > 0$), i.e., if the stock goes up in the aftermarket the investor can get out of the loss domain. The lottery winner will hold the stock if:

$$\begin{aligned} q(x+h) + (1-q)\lambda(x-l) &> \lambda x \\ xq(1-\lambda) + qh + (1-q)\lambda(-l) &> 0 \end{aligned}$$

Next, consider the case in which the listing gain is positive, but aftermarket losses on the stock could put the lottery winner in the loss domain ($l > x > 0$). The lottery winner will hold the stock if:

$$\begin{aligned} q(x+h) + (1-q)\lambda(x-l) &> x \\ (1-q)(\lambda-1)x + qh + (1-q)\lambda(-l) &> 0 \end{aligned}$$

Finally, assume that the listing gain is sufficiently positive that even if the stock goes down after listing it will still be above the issue price ($x > l > 0$). The lottery winner will hold the stock if:

$$\begin{aligned} q(x+h) + (1-q)(x-l) &> x \\ qh + (1-q)(-l) &> 0 \end{aligned}$$

Note in the case above that the listing gain always outweighs potential losses, so the loss-aversion piece of the utility function is irrelevant, meaning that the winner holds if there is a positive expected return and sells otherwise.

The following table presents the conditions that determine whether lottery winners and losers hold the IPO stock post-listing across different possible outcomes of the listing gain. To simplify the presentation we assume that $h = l$, so that the stock's expected return is only a function of the probability of the high return ($q$). We also assume that the listing gain is proportional to the movement in the stock price in the aftermarket, i.e., $x = kh$, where $k$ is the coefficient of proportionality. In the final two rows we explicitly calculate the size of the endowment effect by assuming that amongst the population of investors the probability of the high return ($q$) is distributed uniformly on [0,1]. The table simplifies the conditions above based on these assumptions.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Listing Return | $x << 0$ | $x < 0$ | $x = 0$ | $x > 0$ | $x >> 0$ |
| Proportional Returns Assumption | $k < -1$ | $-1 < k < 0$ | $k = 0$ | $0 < k < 1$ | $k > 1$ |
| Winner Hold Condition | $q > \frac{1}{2}$ | $q > \frac{\lambda}{\lambda+1-k(\lambda-1)}$ | $q > \frac{\lambda}{\lambda+1}$ | $q > \frac{\lambda(1-k)+k}{\lambda+1-k(\lambda-1)}$ | $q > \frac{1}{2}$ |
| Loser Hold Condition | $q > \frac{\lambda}{\lambda+1}$ | $q > \frac{\lambda}{\lambda+1}$ | $q > \frac{\lambda}{\lambda+1}$ | $q > \frac{\lambda}{\lambda+1}$ | $q > \frac{\lambda}{\lambda+1}$ |
| Endowment Effect ($q \sim$ uniform(0,1)) | $\frac{\lambda-1}{2(\lambda+1)}$ | $\frac{-\lambda k(\lambda-1)}{(\lambda+1-k(\lambda-1))(\lambda+1)}$ | 0 | $\frac{k(\lambda-1)}{(\lambda+1-k(\lambda-1))(\lambda+1)}$ | $\frac{\lambda-1}{2(\lambda+1)}$ |
| Endowment Effect ($q \sim$ uniform(0,1))$\lambda = 2$) | $\frac{1}{6}$ | $\frac{2}{15}$ | 0 | $\frac{1}{15}$ | $\frac{1}{6}$ |

When the listing gain is either very large or very small (Columns (1) and (5) of the

Table), the model produces the same expressions for the size of the endowment effect. This occurs because the large negative (or positive) listing gain dominates the future outcomes of the stock for lottery winners, and so the effects of loss aversion in the realization utility function cancel out. For example, when there is a large negative listing gain, regardless of whether a lottery winner sells the stock and realizes the listing loss, or holds the stock and eventually realizes the listing loss plus any future gains or losses, this lottery winner will always be in the loss domain. Given this, the effects of loss aversion cancel out and the lottery winner makes the decision of what to do based purely on the realization utility she will get from the stock's performance in the aftermarket. Similarly, if there is a large listing gain, the lottery winner is never worried about incurring losses, so again she just decides whether to hold or sell based on the future expected return on the stock. However in this case, the effects of loss aversion do not cancel out for lottery losers, as they experience a loss if they buy the stock and it goes down in the aftermarket. This causes lottery losers to be less likely to hold the stock than lottery winners in these cases (i.e. the model is able to generate an endowment effect).

In Column (2) we consider the case of small listing losses, i.e. cases in which the stock's good performance in the after-market could cause the lottery winner to be in the gain domain. Comparing the Winner and Loser Hold Conditions in Column (2), we see that winners require a lower expected return to be willing to hold the stock. Given that the expected return distributions in the winner and loser groups should be equivalent due to the randomization, this implies that the realization utility model also predicts an endowment effect in this case.

Column (3) shows that when the listing gain is zero, the two conditions are the same and we predict no endowment effect.

Finally, Column (4) presents the case where the listing gain is positive but after-market losses could put the lottery winner in the loss domain. Here the model again predicts an endowment effect.

The model generates other predictions that we can use to cross-check against our empirical results. One general prediction is that as the listing gain approaches zero from either above or below, we should see the endowment effect converging to zero. This is because the conditions that determine whether the winner holds the stock converge to the same condition that determines whether the loser holds the stock. In other words, the model predicts that the endowment effect will shrink for listing gains that are small in absolute value. This is the same prediction as for the Weaver-Frederick model.

Inspecting Figure 1 Panels (a) and (b), however, we do not see a pattern of smaller endowment effects for smaller listing gains. And, in our regression analysis we find that the largest endowment effects occur for IPOs with closer to zero gains, and smaller endowment effects for those with either negative or highly positive listing gains. This is an important rejection of this model. The realization utility of agents depends fundamentally on the size of the listing gain, but our empirical results do not find the predicted relationship between the listing gain and the endowment effect. So, while a realization utility model may be useful in explaining lottery winners' tendency to sell winning versus losing IPO stocks in the first month after listing, it does not provide a good explanation for why lottery winners are so much more likely to hold the IPO stock than lottery losers (i.e., the endowment effect).

We now turn to describing a simple model of inattention to check its correspondence with our empirical results.

# F Inattention Model

We consider the simplest possible model of inattention as a beginning. Any such model requires an assumption, in order to generate correspondence with our empirical results, that lottery losers have a sufficiently high cost of paying attention to the IPO stock that they ignore it completely when they lose it, and therefore never buy it in the aftermarket.

One possible microfoundation for this assumption might be that an investor has a constraint on the number of stocks to which they can pay attention. Investors could begin by paying attention to the stocks that they hold, and only consider stocks outside their portfolio once they have devoted sufficient time to their pre-existing holdings. However this is somewhat unsatisfactory, since it assumes that investors would have to incur enormously high costs of paying attention to all new stocks – meaning that the model would generate the prediction of enormous inertia in portfolio holdings. This does not square well with the general finding of high trading volume amongst retail investors around the world, including in the sample of Indian investors.

Another possible microfoundation is offered by Bordalo, Gennaioli, and Shleifer (2015), in which the investor exhibits selective recall, with the "exposure" to a particular stock being very high if the stock is owned by the investor, and zero when the stock is not owned. In this case the random endowment of the stock puts it into the investor's portfolio, resulting in exposure, and therefore attention, while the losers simply fail to pay attention to the stock because it is not in their portfolio.

Turning to modelling lottery winners, there are two contributing factors to their holding the stock after listing. The first is that they are inattentive to the stock. Denote the fraction of winners paying attention to the stock as (a constant) $a$. (We later consider modelling $a()$ as a function of the features of the IPO, such as the listing gain). The second is the investor's private valuation of the stock. In particular, the interaction of these attributes predicts selling behavior – the only investors who sell are those that are simultaneously paying attention to the stock, and believe that it is worth less than the listing price.

Let $\overline{v}$ represent the fraction of winners whose private valuation of the stock is greater than its listing price. Thus, the fraction of lottery winners who hold the stock at the end of the first day are:

$$\bar{v} + (1 - a)(1 - \bar{v}) = 1 - a(1 - \bar{v})$$

Note that given the model assumption that the fraction of losers who hold the IPO stock is zero because they never pay attention, this equation equals the size of the endowment effect. The endowment effect is decreasing in the fraction of attentive investors. The endowment effect is also increasing in the fraction of winners who have higher private valuations than the listing price. This extremely simple model can explain the fact that lottery losers usually do not purchase the stock, and lottery winners tend to hold the stock, but it is worth pointing out that the assumptions required to generate this result are very strong.

We can increase the realism of this model by making the attention function depend on features of the IPO that are likely to attract attention. For example, one possibility is that the attention function depends on the absolute value of the listing gain, $a(|x|)$.The endowment effect under this assumption would be $1 - a(|x|)(1 - \overline{v})$.When the absolute value of the return is large, we should expect smaller endowment effects. In our regression results we do find that IPOs with large negative returns and large positive returns, appear to have smaller endowment effects on the day after listing, consistent with this type of attention model.

Over the longer run we see that the endowment effect appears to reduce significantly for highly positive return stocks, but not for negative return stocks. To explain these results, the model would need an attention function of the form $a(r)$, where the investor pays greater attention to better performing stocks in your portfolio. However it is worth pointing out that this result is somewhat contradictory to the broader literature (see, for example, Barber and Odean (2008), and Hartzmark (2015)), who find that investors tend to pay more attention to (and trade) both the best and worst performing stocks in their portfolios.

The final model we consider, in the next section, is a model of a salience-based decision maker a la Bordalo, Gennaioli, and Shleifer (2012) facing the decision of whether to buy, sell, or hold the stock.

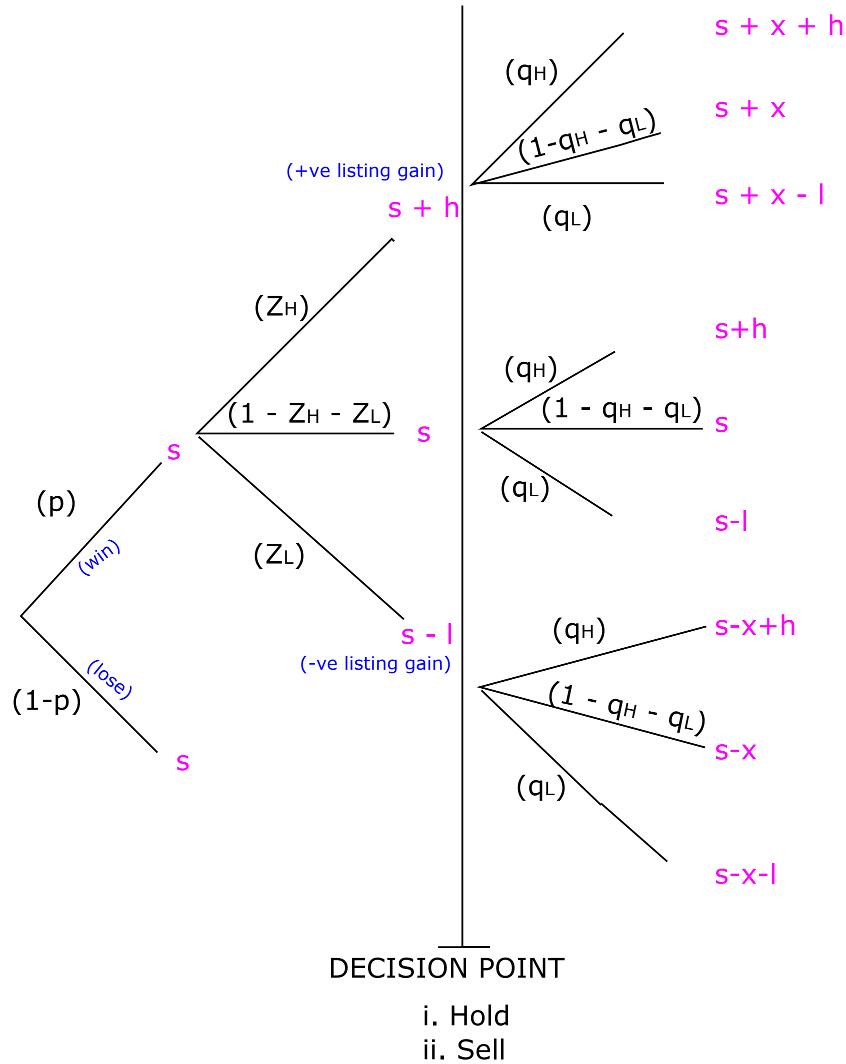
# G Salience Model

We are now interested in modeling the choices of winners and losers immediately *after* the listing gain is realized, under the assumption that the agent is a salience-based decision maker who distorts payoffs as described in Bordalo, Gennaioli, and Shleifer (2012). We consider two variants of the salience model, one which focuses on the behavior of lottery winners after allotment, and a second that studies both winners and losers after allotment. The first model predicts lottery winners will react to experienced returns in a way that is quite consistent with our empirical results, and motivates us to consider salience more broadly as an explanation of the endowment effects we observe. The second model considers a salience-based decision maker who has applied to the lottery but does not yet know their outcome, and calculates how the probability distortions of different outcomes (i.e. winning or losing the lottery, the stock going up or down, etc.) would be calculated. Note that in both models, we do not consider the role of loss aversion, so gains and losses are viewed symmetrically. This is so that we can clearly understand the pure role of belief distortions in explaining our results.

## G.1 Salience Model, Sequential Decisions, Gain-Loss Utility[22]

The investor faces probability $p$, $1-p$ of winning or losing the initial lottery, and then probabilities $z_H$, $1-z_H-z_L, z_L$ of experiencing a high, low, or zero initial listing gain. Finally, the investor faces probabilities $q_H$, $q_L$, and $1-q_H-q_L$ of aftermarket returns being high, low, or zero. The decision tree below shows the assumptions embedded in the model and the agent's decision process.

[22] We thank Nicola Gennaioli for suggesting this setup.




We make several further assumptions here. First, we assume that the investor is a pure gain-loss decision maker, with utility given by returns, rather than by final wealth levels. For simplicity, we assume that utility is linear in gains and losses, using a reference point for measuring gains and losses of zero, and exhibiting no loss aversion. Second, we assume that the decision point in the decision tree above is immediately following the realization of the listing gain. That is, we will model decisions conditional on having experienced a positive or negative listing gain and contrast the decisions of the agent in those two different forks in the decision tree. We later explore the importance of these two assumptions to our final results, and find that both these features are necessary to deliver an endowment effect.

Third, to simplify calculations we assume that $z_H = 1 - z_H - z_L = \frac{1}{3}$and that $q_H = q_L = 1 - q_H - q_L = \frac{1}{3}$. The results will be similar, assuming that any probability distribution as the salience distortion functions only change relative probabilities. Finally, we assume that $x > h = l$ to model the case of the short-run decision following the listing gain. We also assume that the listing gain is symmetric around zero, i.e., the listing loss is $-x$.

We begin by characterizing the decisions of the lottery winners, who hold the stock, and then discuss the behavior of losers (and thus the endowment effect, the empirically observed difference between the two) subsequently.

### G.1.1 Case 1: Positive listing gain

We begin by considering the case of a positive listing gain of $x$. The agent can choose to either sell the stock and realize the gain of $x$ regardless of the state of the world, or hold the stock and realize gains of $(x + h, q_H; x, 1 - q_H - q_L; x - l, q_L)$. The salience-based distortion is computed as follows, using the standard salience function of Bordalo et al. (2012):

| | Payoffs–> | Sell | Hold | $\sigma(y_s^i, y_s^{-i})$ | Salience Ranking |
|---|---|---|---|---|---|
| | True Probability | Gain/Loss | Gain/Loss | | |
| Stock↑ | $q_H = 0.33$ | $x$ | $x + h$ | $\frac{h}{2x+h+\theta}$ | 2 |
| Stock → | $1 - q_H - q_L = 0.33$ | $x$ | $x$ | 0 | 3 |
| Stock ↓ | $q_L = 0.33$ | $x$ | $x - l$ | $\frac{l}{2x-l+\theta}$ | 1 |
| Sum | 1 | | | | |

| Salience $\delta$ | Weighted $\delta$ | Distortion Factor | Distorted Prob. |
|---|---|---|---|
| $\delta^{k_s^i}$ | $\delta^{k_s^i}\pi_s$ | $w_s^i = \frac{\delta^{k_s^i}}{\Sigma_r \delta^{k_r^i}\pi_r}$ | $\pi_s^i = \pi\ w_s^i$ |
| $0.5^2 = 0.25$ | 0.0825 | 0.866 | 0.286 |
| $0.5^3 = 0.125$ | 0.04125 | 0.433 | 0.143 |
| 0.5 | 0.165 | 1.732 | 0.571 |
| | 0.28875 | | |

Note that we once again set the value of the parameter $\delta$, which indexes the extent to which the decision maker is affected by salience, to equal 0.5. In this case, the negative state is salient for the agent experiencing a high gain on the stock, meaning that the expected gain on the stock is negative. The model predicts that the agent will choose to sell the stock following positive returns.

### G.1.2 Case 2: Negative listing gain

Next, consider the case of a negative listing gain of $-x$. The agent can choose to either sell the stock and realize the loss of $-x$ regardless of the state of the world, or hold the stock and realize gains of $(-x+h, q_H; -x, 1-q_H-q_L; -x-l, q_L)$. The salience-based distortion is computed as follows:

| | Payoffs–> | Sell | Hold | $\sigma(y_s^i, y_s^{-i})$ | Salience Ranking |
|---|---|---|---|---|---|
| | True Probability | Gain/Loss | Gain/Loss | | |
| Stock $\uparrow$ | $q_H = 0.33$ | $-x$ | $-x+h$ | $\frac{h}{2x-h+\theta}$ | 1 |
| Stock $\rightarrow$ | $1-q_H-q_L = 0.33$ | $-x$ | $-x$ | 0 | 3 |
| Stock $\downarrow$ | $q_L = 0.33$ | $-x$ | $-x-l$ | $\frac{l}{2x+l+\theta}$ | 2 |
| Sum | 1 | | | | |

| Salience $\delta$ | Weighted $\delta$ | Distortion Factor | Distorted Prob. |
|---|---|---|---|
| $\delta^{k_s^i}$ | $\delta^{k_s^i}\pi_s$ | $w_s^i = \frac{\delta^{k_s^i}}{\Sigma_r \delta^{k_r^i}\pi_r}$ | $\pi_s^i = \pi \ w_s^i$ |
| 0.5 | 0.165 | 1.732 | 0.571 |
| $0.5^3 = 0.125$ | 0.04125 | 0.433 | 0.143 |
| $0.5^2 = 0.25$ | 0.0825 | 0.866 | 0.286 |
| | 0.28875 | | |

In this case the positive state is now salient for the agent, and the expected gain on the stock is positive . The model predicts that the agent will choose to hold the stock following negative returns. Taken together with the prediction in the case of the positive gain, this means that the agent appears to demonstrate a "disposition effect," i.e., holding losers and selling winners.

### G.1.3 Case 3: Zero listing gain

Next, consider the case of a zero listing gain. The agent can choose to either sell the stock and realize a gain of 0 regardless of the state of the world, or hold the stock and realize gains of $(-x + h, q_H; -x, 1 - q_H - q_L; -x - l, q_L)$. The salience-based distortion is computed as follows:

| | Payoffs–> | Sell | Hold | $\sigma(y_s^i, y_s^{-i})$ | Salience Ranking |
|---|---|---|---|---|---|
| | True Probability | Gain/Loss | Gain/Loss | | |
| Stock ↑ | $q_H = 0.33$ | 0 | $h$ | $\frac{h}{h} = 1$ | 1 |
| Stock → | $1 - q_H - q_L = 0.33$ | 0 | 0 | 0 | 2 |
| Stock ↓ | $q_L = 0.33$ | 0 | $l$ | $\frac{l}{l} = 1$ | 1 |
| Sum | 1 | | | | |

| Salience $\delta$ | Weighted $\delta$ | Distortion Factor | Distorted Prob. |
|---|---|---|---|
| $\delta^{k_s^i}$ | $\delta^{k_s^i}\pi_s$ | $w_s^i = \frac{\delta^{k_s^i}}{\Sigma_r \delta^{k_r^i}\pi_r}$ | $\pi_s^i = \pi w_s^i$ |
| 0.5 | 0.165 | 1.212 | 0.4 |
| $0.5^2 = 0.25$ | 0.0825 | 0.606 | 0.2 |
| 0.5 | 0.165 | 1.212 | 0.4 |
| | 0.4125 | | |

In this case the positive and negative states are equally salient for the agent, and the expected gain on the stock is zero in the symmetric case. The model prediction is ambiguous, but we can infer that with a small transaction costs, inaction will be preferred in the case of an intermediate listing gain on the stock. The size of the inaction region will depend on the size of the transaction cost.

### G.1.4 The Role of Experience

The salience model can also naturally incorporate our finding that winners who have experienced more high returns in the past, are more likely to sell the IPO stocks. For an experienced agent, who has invested in multiple stocks and experienced significant returns, we could model their prior beliefs $q_H$, $q_L$ as a function of their experienced returns. For example, if an agent has experienced significantly high (low) returns from past stock investments, we might imagine that $q_H$ for the IPO stock is correspondingly lower (higher) for this agent. That is to say, the historically experienced distribution of returns of the agent might affect the size of $q_H$. Let us first consider the case of an agent who is blasé, having experienced many high returns in the past. In contrast, we will also consider the case of an agent who is a naïf, and very excitable about the listing returns.

For the case of the blasé agent, we would expect that $q_H$ is relatively small, and we can simply (for the sake of generality) assume that $q_L$ stays at 0.33, with $1 - q_H - q_L$ growing correspondingly larger. Blasé agents would sell faster than naïfs after receiving a positive listing gain, and would be slower to sell after negative listing gains. Blasé agents would also be less likely to hold the stock in the case of intermediate returns since their expected returns will be more negative than those of naïfs.

### G.1.5 A note on gain-loss utility

Consider the case of a negative listing gain of $-x$, for an agent who has salience distortions, but considers utility of final payoffs (albeit considered stock by stock). The agent can choose to either sell the stock and realize the stock price of $s-x$ regardless of the state of the world, or hold the stock and realize stock values of $(s-x+h, q_H; s-x, 1-q_H-q_L; s-x-l, q_L)$. The salience-based distortion is computed as follows:

| | Payoffs–> | Sell | Hold | $\sigma(y_s^i, y_s^{-i})$ | Salience Ranking |
|---|---|---|---|---|---|
| | True Probability | Gain/Loss | Gain/Loss | | |
| Stock ↑ | $q_H = 0.33$ | $s-x$ | $s-x+h$ | $\frac{h}{2(s-x)+h+\theta}$ | 2 |
| Stock → | $1-q_H-q_L = 0.33$ | $s-x$ | $s-x$ | 0 | 3 |
| Stock ↓ | $q_L = 0.33$ | $s-x$ | $s-x-l$ | $\frac{l}{2(s-x)-l+\theta}$ | 1 |
| Sum | 1 | | | | |

Notice that the salience ranking in this case has changed – the downside payoff is now most salient, rather than the upside payoff, and the agent will choose to sell in the event of a negative listing return. This reverses the prediction of the simple gain-loss utility case, meaning that the assumption of gain-loss utility is integral to our results.

## G.2 Salience Model, Final Payoffs

### G.2.1 Decision-Making

- The agent is a salience-based decision maker.

- The agent has expectations based reference dependent preferences with loss-aversion (note the salience model and Koszegi Rabin are complements, rather than substitutes, since this model is a model of probability distortion, not value function distortion):

$$u(z|r) = m(z) + \mu(m(z) - m(r)).$$

  In the above, $m(.)$ is consumption utility, and $\mu(.)$ is gain-loss utility relative to the referent, $r$.

- We assume piecewise linear gain-loss utility, i.e.,

$$\mu(y) = \begin{cases} \eta \cdot y & \text{if } y \geq 0 \\ \eta \cdot \lambda \cdot y & \text{if } y < 0 \end{cases},$$

  where $\lambda$ is the degree of loss aversion.

- In this version of the model, we assume that that $\mu = 0$ (pure consumption utility, no gain-loss utility), so $u(y|r) = m(y) = y$.

- Absent any belief distortions, the agent computes expected utility in the usual fashion, i.e., given a probability distribution over $y$ in different states of the world, the agent maximizes:

$$E[u(y)] = \Sigma_s \pi_s y_s.$$

  So for a simple binary lottery with probability $p$ and $1 - p$ for states $y^H$, $y^L$, say, and for a rational decision maker:

$$E[u(y)] = \pi y^H + (1 - \pi) y^L.$$

- For a salience-based decision maker evaluating a given lottery $i$, there is a distortion of probabilities, meaning that $\pi$ is transformed into $\pi_i$. This occurs using a weighting function $w_i$, such that $\pi_i = \pi w_i$.

- $w_i$ is a function of the salience ranking of different states $s$, $k_s^i$.
- $k_s^i$ is obtained from the salience function $\sigma(y_s^i, y_s^{-i})$, which ranks lottery payoffs $y^i$ by comparing all lotteries $i$ for each state $s$.

### G.2.2 Environment

- We assume that all gambles that the agents face are binary as in our earlier models.
- With probability $p$, the agent wins the lottery and receives the stock, and with probability $1-p$, loses and receive cash $c$.
- The value of the stock that the winners receive before the stock lists is $s$. The value of the cash that the losers receive back ($c$) is equal to $s$.
- The stock lists on the exchange at a value $s+x$, where $x$ is the listing gain. This listing gain $x$ is an "instantaneous realized return" on the stock.
- Winners can choose to sell the stock at $s+x$ in the moment after listing.
- Losers can choose to buy the stock at $s+x$ in the moment after listing.
- After the stock lists, the stock price can either go up by an amount $h$ (with true probability $q$) or go down by an amount $l$, with true probability $1-q$. This means that the final price of the stock is $s+x+h$ with probability $q$ and $s+x-l$ with probability $1-q$.
- All decisions are made before the stock realizes its high or low value.
- As before, we begin by assuming that $l < x$, that is the potential loss on the stock after the stock lists is less than the listing gain. We can think of this as a short-run case.

- The agent consumes the value of the stock or cash held at the end of the decision period.

- Exactly as before, there are four possible plans which characterize actions that the agent can take the moment after they learn whether they won the stock, right after it lists (see Table C.3.1).

Our approach is to calculate the salience rankings of the payoffs arising from each of these plans. These payoffs are the payoffs from a compound lottery, conditional on taking the specified actions. The agent applies the salience distortion factor to the objective probabilities of the payoffs occurring, and then computes expected utilities using the distorted probabilities. The agent then picks the plan with the highest utility. Below, we present a series of tables that enable us to compute the salience function and the salience rankings. We use the basic salience function suggested by Bordalo et al. (2012), namely:

$$\sigma(y_s^i, y_s^{-i}) = \frac{|y_s^i - y_s^{-i}|}{|y_s^i| + |y_s^{-i}| + \theta}$$

## G.3 Setup as in our current model

| | Payoffs– > | Plan 1 | Plan 2 | Plan 3 | Plan 4 |
|---|---|---|---|---|---|
| | True Probability | Win ↑ | Win ↓ | Lose ↑ | Lose ↓ |
| Win ↑ | $pq$ | $s+x$ | $s+x+h$ | $s+x+h$ | $s+x$ |
| Win ↓ | $p(1-q)$ | $s+x$ | $s+x-l$ | $s+x-l$ | $s+x$ |
| Lose ↑ | $(1-p)q$ | $s$ | $s+h$ | $s$ | $s+h$ |
| Lose ↓ | $(1-p)(1-q)$ | $s$ | $s-l$ | $s$ | $s-l$ |

| | $\sigma(y_s^i, y_s^{-i})$–> | Plan 1 | Plan 2 | Plan 3 | Plan 4 |
|---|---|---|---|---|---|
| | True Probability | Win ↑ | Win ↓ | Lose ↑ | Lose ↓ |
| Win ↑ | $pq$ | $\frac{\lvert -h\rvert}{2(s+x)+h+\theta}$ | $\frac{\lvert h\rvert}{2(s+x)+h+\theta}$ | $\frac{\lvert h\rvert}{2(s+x)+h+\theta}$ | $\frac{\lvert -h\rvert}{2(s+x)+h+\theta}$ |
| Win ↓ | $p(1-q)$ | $\frac{\lvert l\rvert}{2(s+x)-l+\theta}$ | $\frac{\lvert -l\rvert}{2(s+x)-l+\theta}$ | $\frac{\lvert -l\rvert}{2(s+x)-l+\theta}$ | $\frac{\lvert l\rvert}{2(s+x)-l+\theta}$ |
| Lose ↑ | $(1-p)q$ | $\frac{\lvert -h\rvert}{2s+h+\theta}$ | $\frac{\lvert h\rvert}{2s+h+\theta}$ | $\frac{\lvert -h\rvert}{2s+h+\theta}$ | $\frac{\lvert h\rvert}{2s+h+\theta}$ |
| Lose ↓ | $(1-p)(1-q)$ | $\frac{\lvert l\rvert}{2s-l+\theta}$ | $\frac{\lvert -l\rvert}{2s-l+\theta}$ | $\frac{\lvert l\rvert}{2s-l+\theta}$ | $\frac{\lvert -l\rvert}{2s-l+\theta}$ |

To arrive at the salience ranking from these salience functions, we make a few assumptions.

First, note that we have already assumed that $x > l$, i.e., we are modelling the short-run case. Second, we assume for simplicity that $h = l$ (the case of symmetric payoffs), and $x = kh$, $k > 1$ (proportionality).

Then, when the listing gain is large relative to the gain or loss on the stock, the resulting salience ranking is in the second column in the table below. Our next step is to transform these salience rankings into probability distortions. In order to do so, we need to set the value of the parameter $\delta$, which indexes the extent to which the decision maker is affected by salience. Note that $\delta = 1$ implies a rational decision maker with no salience distortion, and as $\delta \longrightarrow 0$, salience increases. We therefore consider the case of $\delta = 0.5$. We also assume that $p = 0.5$ and $q = 0.5$ for illustrative purposes. For $p = q = 0.5$, all four states (Win up, down, and Lose up, down) are equiprobable:

| | Payoffs–> | Salience Ranking | Salience $\delta$ | Weighted $\delta$ | Distortion Factor | Distorted Prob. |
|---|---|---|---|---|---|---|
| | True Probability $\pi$ | | $\delta^{k_s^i}$ | $\delta^{k_s^i}\pi_s$ | $w_s^i = \frac{\delta^{k_s^i}}{\Sigma_r \delta^{k_r^i}\pi_r}$ | $\pi_s^i = \pi w_s^i$ |
| Win ↑ | $pq = 0.25$ | 4 | $0.5^4 = 0.0625$ | $(0.0625)pq = 0.015625$ | 0.267 | 0.067 |
| Win ↓ | $p(1-q) = 0.25$ | 3 | $0.5^3 = 0.125$ | $(0.125)p(1-q) = 0.03125$ | 0.533 | 0.133 |
| Lose ↑ | $(1-p)q = 0.25$ | 2 | $0.5^2 = 0.25$ | $0.25(1-p)q = 0.0625$ | 1.067 | 0.267 |
| Lose ↓ | $(1-p)(1-q) = 0.25$ | 1 | $0.5^1 = 0.5$ | $0.5(1-p)(1-q) = 0.125$ | 2.133 | 0.533 |
| Sum | 1 | | | 0.234375 | | 1 |

| | Payoffs–> | Plan 1 | Plan 2 | Plan 3 | Plan 4 |
|---|---|---|---|---|---|
| | Distorted Probability | Win ↑ | Win ↓ | Lose ↑ | Lose ↓ |
| Win ↑ | 0.067 | $s + x$ | $s + x + h$ | $s + x + h$ | $s + x$ |
| Win ↓ | 0.133 | $s + x$ | $s + x - l$ | $s + x - l$ | $s + x$ |
| Lose ↑ | 0.267 | $s$ | $s + h$ | $s$ | $s + h$ |
| Lose ↓ | 0.533 | $s$ | $s - l$ | $s$ | $s - l$ |
| Expected Value | (Assume $h = l$) | $s + 0.2x$ | $s + 0.2x - 0.33h$ | $s + 0.2x - 0.067h$ | $s + .2x - 0.267h$ |

In this particular case, the agent should prefer Plan 1 to all other plans – because the Lose down state is the most salient of all it is preferred to Plan 2, and because the Win down state is more salient than the Win up state it is preferred to Plan 3 as well. So we should never see an endowment effect in the equiprobable case.

Note that even if the salience distortion factor goes up a great deal (say $\delta = 0.1$), the agent would always still prefer Plan 1 to Plan 3, since the Win down state will always be more salient than the Win up state. So it is impossible to deliver an endowment effect in the short-run cases for these assumed parameter values. It might well be the case that Plan 3 is preferred in certain cases with different values of $p$ and $q$, but our simple analysis shows that it is difficult for this model to explain our empirically estimated endowment effect.

We now turn to an alternative model setup, in which the agent has pure gain-loss utility, and makes sequential decisions (following the initial IPO lottery) rather than deciding ex-ante faced with the lottery and the choice of whether or not to hold the stock.

### G.3.1 A note on our original setup and gain-loss utility

Consider the case of a salience-based decision maker who considers a broader state-space as in our original setup, i.e. does not make sequential decisions, but rather considers all options ex-ante prior to the IPO lottery. To ascertain the impact of this change, we now go back to the agent with pure gain-loss utility rather than utility of final payoffs. In this case, the salience rankings are:

| | Payoffs–> | Plan 1 | Plan 2 | Plan 3 | Plan 4 |
|---|---|---|---|---|---|
| | True Probability | Win ↑ | Win ↓ | Lose ↑ | Lose ↓ |
| Win ↑ | $pq$ | $x$ | $x+h$ | $x+h$ | $x$ |
| Win ↓ | $p(1-q)$ | $x$ | $x-l$ | $x-l$ | $x$ |
| Lose ↑ | $(1-p)q$ | 0 | $x+h$ | 0 | $x+h$ |
| Lose ↓ | $(1-p)(1-q)$ | 0 | $x-l$ | 0 | $x-l$ |

| $\sigma(y_s^i, y_s^{-i})$–> | Plan 1 | Plan 2 | Plan 3 | Plan 4 | Salience Ranking |
|---|---|---|---|---|---|
| True Probability | Win ↑ | Win ↓ | Lose ↑ | Lose ↓ | |

| | | | | | | |
|---|---|---|---|---|---|---|
| Win ↑ | $pq$ | $\frac{h}{2x+h+\theta}$ | $\frac{h}{2x+h+\theta}$ | $\frac{h}{2x+h+\theta}$ | $\frac{h}{2x+h+\theta}$ | 3 |
| Win ↓ | $p(1-q)$ | $\frac{l}{2x-l+\theta}$ | $\frac{l}{2x-l+\theta}$ | $\frac{l}{2x-l+\theta}$ | $\frac{l}{2x-l+\theta}$ | 3 |
| Lose ↑ | $(1-p)q$ | $\frac{x+h}{x+h+\theta}$ | $\frac{x+h}{x+h+\theta}$ | $\frac{x+h}{x+h+\theta}$ | $\frac{x+h}{x+h+\theta}$ | 1 |
| Lose ↓ | $(1-p)(1-q)$ | $\frac{x-l}{x-l+\theta}$ | $\frac{x-l}{x-l+\theta}$ | $\frac{x-l}{x-l+\theta}$ | $\frac{x-l}{x-l+\theta}$ | 2 |

This looks no different from the ranking in the previous version of the model, so it seems clear that this change will not affect those conclusions, i.e., the model does a poor job or explaining winners' behavior. Once again, it appears that the assumption of sequential decision making is important to help explain the results for winners' behavior.

## G.4 Can the Salience Model Explain the Endowment Effect?

The calculations above show that, for lottery winners, the salience model can explain two important empirical facts in our data. First, lottery winners have an increasing tendency to sell the stock during the first month as the returns on the stock get larger. The model produces this result because agents in the salience model distort upwards the probability of a rebound when the stock has a negative listing gain, and distort upwards the probability of a downturn in the stock when the stock has a large positive listing gain. Second, the model can explain the relationship between previously experienced returns and the behavior of lottery winners. Given this, we now discuss to what extent a salience model can explain the fact that lottery winners are so much more likely to hold the IPO stock than lottery losers (i.e., the endowment effect).

We first note that if lottery losers are paying attention to the listing gains of the IPO stock, and they are salience based decision makers, then they should have the same distorted probabilities regarding the future returns of the stock that the lottery winners have. In this case, lottery losers should be more likely to buy the stock when the listing gain is low, because a rebound in the stock price is the salient future outcome (just as lottery winners are more likely to hold the stock when the listing gain is low). And, when the listing gain is high, we should see relatively fewer lottery losers buying the stock as the salient future outcome on the stock is the down state. Empirically, however, we do not see an downward sloping relationship between the IPO's listing return and the propensity of the lottery losers to buy the stock. This suggests that the features of this model that explain the winner's selling behavior in the after-market are not sufficient to explain the loser's behavior.

For this type of model to explain the results, we need to add at least one additional assumption that the listing gains distorts future return probabilities in a systematically different way for lottery winners and losers. Perhaps the simplest assumption would be that lottery losers ignore the listing gain, and therefore think about the IPO stock on the first day of trading as if they had experienced a zero return in the IPO stock. Under this assumption, the agent losing the lottery faces a very similar decision to a lottery winner who holds the stock and experiences a zero listing gain. This is because the design of the lottery means that the losing agent makes an effective gain/loss of zero relative to their initial investment in the IPO lottery. The losing agent effectively faces only the second stage of the lottery in which the aftermarket gain or loss is evaluated in an analogous fashion to the zero listing gain case above. In this case, with a small transactions cost of entering into the stock, we could generate non-entry for lottery-losing agents. The important point, however, is that this requires an additional assumption regarding whether lottery losers are paying attention to the IPO stock – i.e., a "hybrid" salience and inattention model is required to explain the endowment effect observed in the empirical results.