The Effects of Experience on Investor Behavior

Evidence from India's IPO Lotteries

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Motivation

- Standard economic models predict negligible role for personal experience in future decision making.
  - Especially in high public information environments (e.g., stock market).
- Newer models explore implications of personal experience:
  - Reinforcement learning - Roth and Erev (1995).
  - Reference dependent risk-attitudes - Koszegi and Rabin (2007).

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- Newer models explore implications of personal experience:
  - Reinforcement learning - Roth and Erev (1995).
  - Reference dependent risk-attitudes - Koszegi and Rabin (2007).
- Empirical literature suggests personal experience is important:
  - Long-term: Experiences of Great Depression lowers risk-taking - Malmendier and Nagel (2007).
  - Short-term: Portfolio experiences correlate with future decisions - Barber and Odean (2013).
- Challenge: Personal experiences are endogenous with observed changes in behaviour.
  - Changing skill, beliefs, preferences, rational learning.

This Paper

- New research design to estimate experience effects.
  - Randomized variation in portfolio experiences from Initial Public Offering (IPO) lottery outcomes.
  - IPO lottery method could be applied to many other contexts.

    Countries: Brazil, China, Germany, Hong Kong, Singapore, Sweden, Taiwan; U.S. brokerages (TD Ameritrade, Fidelity).
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- New facts on how experiences **cause** changes in investment behavior.
- Very high level of detail allows precise estimates of heterogeneous effects; better understanding of mechanisms:
  - Across stocks: Spillover effects to rest of portfolio ("within portfolio contagion").
    - Strength of the experimental approach, greater confidence as domain of effects widens.
  - Across (1.5 MM) investors: Effects significant even with small treatments for large/experienced investor portfolios.

The Indian IPO Lottery Process: Allocations

- Firm chooses issue price, implies subscription ratio:

$$r = \frac{\text{Retail Demand}}{\text{Retail Supply}}$$

- Three possible outcomes after issue price chosen:
  - $r \leq 1$
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    - $\rightarrow$ Retail bidders are allocated proportionally (no lotteries).
  - $r >> 1$ and proportional allocation leads to retail bidder receiving $<$ min lot size
    - $\rightarrow$ **Lotteries used so that winners get min lot size, losers get nothing.**
    - Analysis focuses solely on this relatively common case.
    - Mean subscription rate in our 54 IPO sample is 12.

The Indian IPO Lottery Process: Example

- Assume 10,000 shares available for retail investors.
- Assume investors can bid for 100, 200, or 300 shares ("share category")
- Minimum allocation is 100 shares.
- Assume demand at final price is 40,000 shares ($r = 4$).

Share Category (1)	Total # Applications (2)	Total Demand (3) = (1)*(2)	Total Allocated (4)=(3)/r	Proportional Allocation (5)=(4)/(2)	Win Probability (6)	Winner Allotment (7)
100	200	20,000	5,000	25	.25	100
200	88	17,600	4,400	50	.50	100
300	8	2,400	600	75	.75	100
Total		40,000	10,000			

- Win probability → proportional allocation received in expectation.
  - Winners get minimum lot size, losers receive no shares.
- Each IPO share category is a randomized control trial
  - In this example, 3 experiments.
  - Our sample has 383 such experiments (323 with positive returns).

Data

- IPO Applications:
  - 1.5 million retail applications to 54 IPOs from 2007 - 2012.
  - Data provider handled 8% of value of all IPOs in this period.
  - Observe # shares applied for, # shares allocated, zip code, cutoff bid.
- Monthly Portfolio Data:
  - 12 million accounts over period 2002 - 2012.
  - Full data covers 40% of Indian retail investor accounts.
  - Match to IPO applications using anonymized account #.
  - Observe full portfolio at end of month, total value and number of shares bought and sold in each month.
- IPO Characteristics
  - First day returns, industry, etc.

Characterizing the Treatment Experience

Treatment Characteristics		Percentile Across Experiments				
	Mean	10	20	50	75	90
	(1)	(2)	(3)	(4)	(5)	(6)
Application Amount ($)	1803	163	392	846	1524	2174
Probability of Treatment	0.35	0.09	0.18	0.35	0.63	0.82
Allotment Value ($)	150	123.8	134	145	157	165
First Day Gain (%)	42	6.0	11.5	21.7	40.0	87.8
First Day Gain ($)	67	8.6	14.3	29.6	65.3	141.6
Median Portfolio Value ($t-1$, $)	1866	805	1126	1632	2466	3208

Notes: Includes 40 positive return IPOs (323 share categories) in sample. Treatment and control sample sizes are 433,042 and 1,040,031 accounts respectively.

- Small treatments on average
  - Gain is $\approx$ 1.8 percent (experimental median treatment/median portfolio size pre-experiment).
  - On average, treat/control put down $1,800 for 1st day gain of $67.

Summary Statistics and Randomization Check

Portfolio and Trading Value

	Treatment	Control	Difference	% Experiments $>$ 10% significance
	(1)	(2)	(3)	(4)
IHS(Portfolio Value)	6.575	6.573	0.002	13.00
0	0.222	0.221	0.000	10.52
0 to 500$	0.143	0.143	-0.001	8.66
500 to 1000$	0.097	0.097	0.000	8.63
1000 to 5000$	0.285	0.285	0.000	9.59
$>$ 5000 $	0.252	0.252	-0.001	10.21
IHS(Gross Transaction Value)	5.619	5.616	0.003	11.45
0	0.287	0.288	-0.001	8.97
0 to 500$	0.183	0.183	-0.001	9.90
500 to 1000$	0.127	0.127	0.000	9.59
1000 to 5000$	0.287	0.285	0.002**	14.55
$>$ 5000 $	0.116	0.117	-0.001*	8.97

Notes: Includes 40 positive return IPOs (323 share categories). Treatment (control) sizes are 433,042 (1,040,031) accounts. All variables defined as of month prior to the treatment IPO. IHS = Inverse-hyperbolic sine transformation.

Estimating Treatment Effects

- Compare treatment and control accounts in the 6 months prior to and following treatment.
- Cross-sectional regression in each event-time period:

$$y_{ij} = \beta_0 + \beta_1 T_{ij} + \eta_j + \epsilon_{ij}.$$

  - y_{ij} is outcome variable of interest for investor i in share category j.
  - T_{ij} = treatment dummy, η_j IPO share category fixed effect.
- Specification **only** uses randomized variation within experiment.
  - β_1 = weighted average of experiment treatment effects (Angrist 1998).
- Expect $\beta_1 = 0$ for months before treatment (placebo test).
  - All outcomes we will see exclude IPO treatment stock.

Effect on Probability of Applying for IPOs

Placebo Test: Six Months Prior to Treatment

	Month Relative to Treatment IPO					
	-6	-5	-4	-3	-2	-1
Treatment Effect	0.0006	0.0018**	0.0003	0.0005	-0.0009	-0.0001
	(0.0008)	(0.0009)	(0.0012)	(0.0008)	(0.0006)	(0.0010)
Control Mean:	[0.2034]	[0.3108]	[0.2043]	[0.2172]	[0.3324]	[0.3786]

Notes: Dependent variable = 1 if account applied for IPO in our data or was allotted IPO not in our data in month. Observations = 1,473,073; # Share Categories = 323; # IPOs = 40. Sample includes only positive return IPOs.

- No strong relationship between treatment and probability of applying to IPOs *prior to treatment.*
    - Holds for all outcomes we study (see paper for details).

Effect on Probability of Applying for IPOs

	Month Relative to Treatment IPO					
	1	2	3	4	5	6
Treatment Effect	0.0094***	0.0071**	0.0029**	0.0019**	0.0032**	0.0013
	(0.0015)	(0.0030)	(0.0015)	(0.0009)	(0.0012)	(0.0011)
Control Mean	[0.4636]	[0.2242]	[0.1283]	[0.0959]	[0.1341]	[0.0605]

- Small but significant impact on future IPO participation. (Kaustia and Knupfer, 2008).
- Likely underestimate as we only observe allotments, not applications, to most future IPOs (in progress).
- Next, we look at **portfolio-wide** effects – a *causal* estimation enabled by our experimental setup.
  - But first, a quick digression on estimating learning models.

Treatment Effects at Share Category Level

BGR Share Category	Share Category of Outcome IPO: Future Capital Holdings Limited															
	8	16	24	32	40	48	56	64	72	80	88	96	104	112	120	128
14	.191	.034	.000	.009	-.001	-.001	.000	.004	-.003	-.003	-.001	-.002	-.001	.000	-.001	-.025
28	.032	.112	.028	.013	-.003	-.002	-.005	-.006	-.005	-.005	.001	-.001	.001	-.001	-.002	-.021
42	.006	.028	.063	.011	.011	.004	-.003	-.001	.002	.001	-.003	-.004	-.003	-.002	.001	-.017
56	-.006	.017	.031	.059	.013	.001	.020	.004	.003	-.004	.001	.002	-.003	.002	.000	-.025
70	.005	.012	.002	.022	.041	.018	.010	.016	.004	.000	-.002	.003	-.003	-.002	-.001	-.019
84	.002	.013	.009	.013	.013	.010	.018	.020	-.006	.001	.004	.007	-.003	-.003	-.003	-.003
98	.002	.003	.004	.014	.005	.007	.006	.061	.001	-.002	.002	.001	.000	.002	-.002	-.025
112	-.005	-.002	.005	.009	.007	.002	.006	.009	.043	.010	.005	-.002	.003	-.002	.002	-.023
126	-.009	.006	-.006	.015	.003	.015	.010	.011	.029	.019	.012	.009	.009	-.003	-.005	-.030
140	.002	.002	.006	.005	.007	.002	.004	.009	.006	.050	.020	.004	.001	-.002	-.005	-.038
154	-.008	.002	-.010	.002	.001	.006	.003	-.001	.001	.023	.012	.036	.015	.007	.013	-.030
168	-.002	-.002	.004	-.004	-.011	.005	.010	.019	.006	.013	.010	.018	.019	.008	-.011	-.009
182	-.001	-.002	.003	.001	-.005	-.004	-.002	-.002	-.007	-.005	.013	.013	.022	-.002	.037	.005
196	-.001	-.001	-.001	.000	.000	.000	-.001	.000	.000	.001	.000	.000	.000	.000	.000	.031

Notes: Treatment IPO is BGR Energy Systems. Numbers in table give the treatment effect of getting allotted in the BGR lottery on the probability the investor applies to a specific share category in the Future Capital Holdings IPO. Green: positive and significant at 10% level. Red: negative and significant at 10% level.

- Green (diagonal): Experience effects largely concentrated on diagonal (win-stay?).
- Red (upper-right): Control group more likely to apply for large amounts of shares - strategic learning about probabilities (lose-switch).
- Red (lower-left): Losers who applied for a lot of shares switch to fewer (lose-switch).

Effect on Portfolio Weight in Treatment IPO Sector

	Months After IPO Treatment					
	1	2	3	4	5	6
Panel A: Dummy(Hold Stock in IPO Sector)						
Treatment Effect	0.0006	0.0010	0.0013	0.0018	0.0015	0.0016
	(0.0014)	(0.0013)	(0.0013)	(0.0014)	(0.0015)	(0.0011)
Control Mean	[0.3662]	[0.3966]	[0.3946]	[0.4038]	[0.4109]	[0.4063]
Panel B: Portfolio Weight IPO Sector						
Treatment Effect	0.0001	0.0005**	0.0008***	0.0009**	0.0008***	0.0006***
	(0.0004)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0002)
Control Mean	[0.0708]	[0.0822]	[0.0811]	[0.0823]	[0.0851]	[0.0808]

Notes: Sector definitions based on 42 sector NIC code. Observations = 1,473,073; # Share Categories = 323; # IPOs = 40. Treatment IPO sectoral breakdown: 54% manufacturing, 31% services, 7% technology and 4% other. Dependent variable excludes treatment IPO stock.

- Small but significant effect on portfolio weight in IPO sector (extrapolation, Greenwood et al., 2015).

Effect on Gross Trading Value in Non-IPO Stocks

	Months After IPO Treatment					
	1	2	3	4	5	6
Treatment Effect	0.0746***	0.0742***	0.0447***	0.0333***	0.0345***	0.0345***
	(0.0121)	(0.0082)	(0.0118)	(0.0083)	(0.0089)	(0.0066)
Control Mean	[1.5832]	[0.9868]	[0.3052]	[0.2147]	[0.4525]	[0.2522]

Notes: Dependent variable = IHS(buy value + sell value in month) and excludes the treatment IPO stock. Observations = 1,473,073; # Share Categories = 323; # IPOs = 40. Sample includes only positive return IPOs.

- Treatment group trades substantially more in **non-IPO** stocks:
  - 7.5% more in two months after treatment.
  - 3.5% more trades six months out.
- Portfolio re-balancing?
  - Small treatment size, 6 months of trading.
  - Find negative effect on trading for IPOs w/ negative returns (more later).
- Implications:
  - Cross-security, within portfolio experience effects important.

Treatment Effect Heterogeneity

By Listing Day Returns

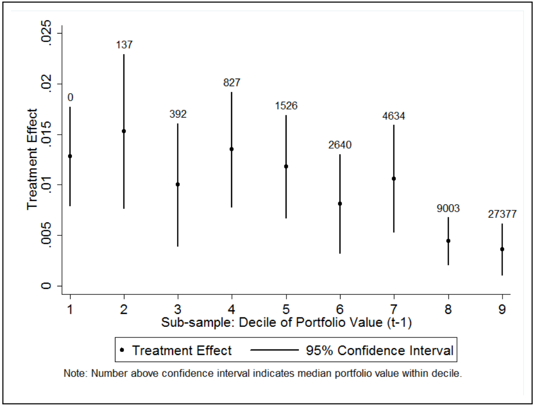
IPO Sample:	Positive Returns (1)	Negative Returns (2)
1. Future IPO Participation	0.0117***	-0.0142**
Time: (t+1) to (t+6)	(0.0013)	(0.0039)
2. Gross Transaction Value	0.0717***	-0.0210
Time: (t+1) to (t+6)	(0.0071)	(0.0192)
3. Propensity to hold IPO sector stocks	0.0022	-0.0064**
Time: (t+1) to (t+6)	(0.0015)	(0.0029)
4. Weight in IPO sector	0.0006***	-0.0011**
Time: (t+6)	(0.0002)	(0.0064)
5. Portfolio value > 0	0.0013***	0.0012
Time: (t+1) to (t+6)	(0.0004)	(0.0014)
6. Portfolio value	0.0089	-0.0154
Time: (t+6)	(0.0075)	(0.0209)
Observations	1,473,073	89,637

Notes: 14 IPOs (40 share categories) with negative returns. 40 IPOs (323 share categories) with positive returns.

Treatment Effect Heterogeneity by Portfolio Value

Probability of Applying to Future IPO

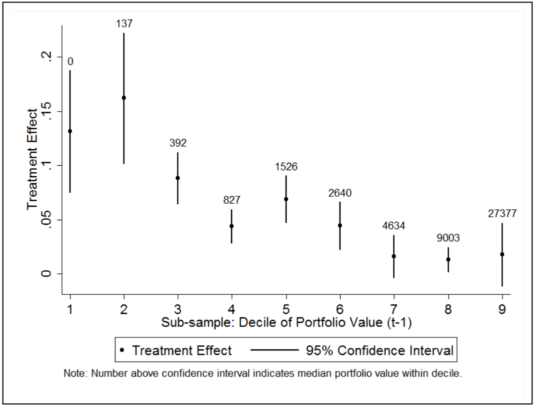
- Sample split into deciles based portfolio value in month before IPO
- Estimate separate treatment effects for each decile



- IPO application treatment effect similar for portfolio values for portfolio values 0 to 5,000 dollars (1st 8 deciles).
- Significant positive effects even for highest decile.

Treatment Effect Heterogeneity by Portfolio Value

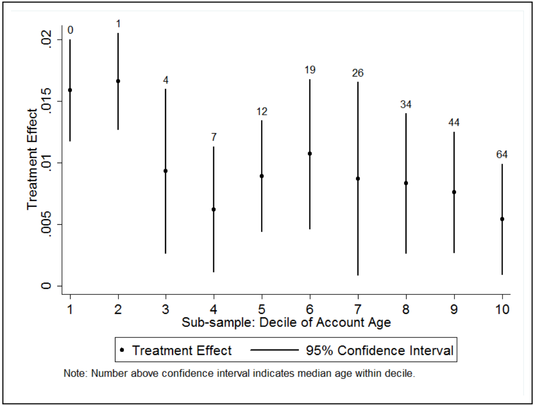
IHS(Gross Trading Value)



- Effect declines with portfolio value.
- Significant effects even for highest decile.

Treatment Effect Heterogeneity by Account Age

Probability of Applying to Future IPO



- Bigger effects for new accounts, no major pattern in older accounts.
- Similar results for other outcomes. Age in the market attenuates effects, but not completely (List, 2011).

Conclusion

- New research design to identify experience effects.
- Experience of portfolio gain in randomly assigned IPO stock causes:
  - Small, but significant increases in IPO investment and sectoral allocation.
    - Changes in beliefs about the sectoral source of experience.
  - Large increase in trading activity accompanied by an increase in the disposition effect.
    - Not just overconfidence, suggests reference-dependent utility.
    - Luck as skill less likely than, luck as evidence of "being lucky".
- Difficult to explain results based on wealth or rebalancing effects.
- Implications (Work underway):
  - Narrow vs. portfolio framing → within portfolio contagion effects.
  - Reference-dependent risk preferences.
  - "Learning" to bid (win-stay, lose-switch a la Roth and Erev (1995)).