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Abstract

We design an experiment where subjects must choose between a risky investment, which evolves according to an autoregressive process, and a risk-free investment which has a constant payoff. The treatments vary the information available on the risky investment when players choose the risk-free alternative. We find that in the public information treatment, which captures the information structure of index funds, subjects stay out of the market longer compared to the private information environment, which captures elements of private equity investment. The difference in behavior across treatments can be explained by the demand for information, which appears to overcome risk aversion.

Keywords: forecasting experiment, investment decisions, market timing, discrete choice

JEL codes: D81, D83, D84, G11, G170, C91

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1 Introduction

The decision to participate in a stock market is often influenced by prior experience, where investors who suffer losses are less willing to participate (Malmendier and Nagel, 2011; Amromin and Sharpe, 2013). Furthermore, investors seem to be optimistic during booms and pessimistic during downturns, potentially due to time-varying risk preferences, learning processes (Adam et al., 2017) or deviations from rational expectations (Greenwood and Shleifer, 2014).[1] However, most of these studies evaluate investor behavior when information is publicly available (e.g. the stock market). When information is not publicly available, as is the case for hedge funds and venture capital projects, the empirical evidence is rather scarce. We conduct a laboratory study to investigate how investor behavior, in our case market participation, varies according to different information disclosure rules.

In our experiment the investment choice consists of two options: (i) a risky asset (such as a stock), which yields a payoff that is governed by an autoregressive (AR) process, or (ii) a risk-free asset (such as a bond), which yields a constant payoff. The participants can switch between investing in a risky asset (IN) and a risk-free asset (OUT) as many times as they like over the course of a round, which lasts for 160 periods. In the public information treatment, the environment is similar to a market timing task (Henriksson and Merton, 1981; Treynor and Mazuy, 1966) where the fund manager must predict when the risky asset will outperform the risk-free asset and vice versa. In this treatment, the subjects have access to information on the payoff of the risky asset, regardless of which investment option is chosen. In the private information treatment, the subjects who opt for the risk-free option lose access to information on risky assets. We study market participation decisions by analyzing the choice between IN and OUT while controlling for the underlying value of the risky project. In order to obtain a clean comparison across treatments, we adopt the same autoregressive process for IN in both public and private information environments.

The process of expectations formation is important for predicting market participation

[1] There is also evidence of asymmetric learning across gains and losses, which affects future participation in risky projects (Kuhnen, 2015; Kuhnen and Miu, 2017).

in our environment, where subjects choose whether to invest in a risky asset or a risk-free option. These investment decisions are likely driven by beliefs about the relative payoff of the two investment strategies.[2] Thus, a good starting point for predicting expectations formation of subjects are behavioral rules with empirical support and which have demonstrated superior explanatory power relative to Rational Expectations (RE). Such rules include sticky expectations (Coibion and Gorodnichenko, 2015; Bouchaud et al., 2019), and extrapolative expectations (Bordalo et al., 2018).[3] Landier et al. (2019) find evidence of both sticky and extrapolative expectations in an experiment where subjects were asked to forecast 40 realizations of a risky asset. Our environment provides a richer information set, given that the payoff process for the risky asset is updated every half a second, for 80 seconds (160 ticks) per round. However, we do not elicit expectations.[4] In our experiment, we would like to the extent possible, provide a continuous and dynamic setting to the subjects. This environment becomes especially salient in the private information treatment, where subjects lose access to the payoff of IN strategy when choosing OUT. Further, the unique task of switching across investment choices reduces the fatigue from entering multiple forecasts.

We also consider a possible link between risk preferences and decisions of subjects. Using survey data Guiso et al. (2018) find that after 2008 financial crisis, individuals who experienced an increase in risk aversion were four times more likely to sell their stock holdings in a downturn. Analogously, this can be viewed as people opting OUT of the market in our experiment. Cohn et al. (2015) find similar behavior in terms of market participation in experiments with financial professionals who are primed with either booming or bearish markets. However, König-Kersting and Trautmann (2018) conclude that priming student subjects does not affect investment decisions.[5] In our environment, the time-varying risk

[2]For a recent study of laboratory asset markets and trader strategies please refer to Carlé et al. (2019) and for price dynamics and forecasts to Hommes et al., 2004.

[3]For empirical evidence using expectations survey data, please refer to Amromin and Sharpe (2013), Wen (2018) and Gennaioli et al. (2016).

[4]There is a large experimental literature on expectation formation where the predicted variable is exogenous (e.g. historical stock prices). For more information see Schmalensee (1976), Dwyer et al. (1993), Hey (1994), Kelley and Friedman (2002), Glaser et al. (2007), and Beshears et al. (2013).

[5]Schwaiger et al. (2019) present evidence that price expectations of the professional traders are less prone to framing effects relative to students.

preferences appear when the investor delays the decision to enter/exit the market and bears the risk of a lower payoff. We estimate a discrete choice model[6] (Anderson et al., 1992) and show that our data, on aggregate, supports risk neutrality of subjects across both treatments.

To formulate our hypothesis, we use comparative statics from behavioral expectations formation rules and behavioral outcomes from previous field and experimental studies. According to behavior known as the "ostrich effect" (Karlsson et al., 2009; Sicherman et al., 2015 and for an overview of the literature, Golman et al., 2017), subjects in our experiment may avoid information and disproportionately opt for the risk-free investment. This behavior reinforces the predicted comparative statics across treatments under the forecasting rules that we apply.[7] The intuition is based on the mean-reversion process that governs the evolution of the risky payoff. In the public information treatment, subjects are more likely to observe the risky investment payoff approaching the mean, which should motivate them to select IN more often compared to the private information treatment where the mean payoff is harder to determine. Alternatively, selecting OUT in the private information treatment can be viewed as costly since players lose access to information on the payoff process of the risky investment. Thus, in the private information treatment players may choose to participate in the market by selecting IN more often. If the impact of informational demand is substantial, it can reverse the outcome predicted by comparative statics.

Our results support the importance of informational demand in the private information treatment. We find that subjects experience shorter OUT spells, or rejoin the risky project sooner, in the private information treatment. This result persists when we limit our data set to the later rounds of the experiment. Thus, our experiment reveals that (i) subjects seek to remove the uncertainty of the risky project through active participation, and (ii) lack of information does not appear to impede market participation in an otherwise similar environment. When information on the forgone payoff is available, as in the public information treatment, subjects opt out of the risky investment at higher rates. Thus, low payoff outcomes in risky

[6]Please refer to Appendix C for more information.

[7]The predicted treatment differences are robust even when we assume risk-averse rather than risk-neutral investors.

projects (whose evolution is governed by a mean-reversion process) appears to deter investors only when the information on the forgone payoffs is publicly available.[8]

Our experimental design aims to capture participation rate across risky and safe assets. We assume that all players are price-takers who face the binary choice IN or OUT — with similarities to stop-loss strategies in financial markets.[9] We find that players exit the market when the risky investment is near the risk-free option in the public information environment and wait slightly longer in the private information environment. The difference is small but significant and captures the demand for information in the private information treatment. The decision to wait to exit the market resembles the option values in irreversible decisions in the lab (Oprea et al., 2009; Rabanal, 2014).

The dilemma between exploiting the safe option and exploring the risky option is also known as a bandit problem, which has a broad application in economics and finance (Bergemann and Välimäki, 2008). In a typical bandit problem the payoff to the risky arm is not known unless exercised, and in the restless bandit problem the payoff distribution may vary, as is the case in our experiment. While selecting the risky arm may be costly, Banks et al. (1997) find that subjects see a value in obtaining more information. Further, in a two-armed restless bandit problem, Biele et al. (2009) determine that players do not learn to become risk averse.[10] Our results seem to support this notion. Prior studies do not offer a clear consensus on the effect of counterfactual information on risk-taking behavior in bandit problems. While Grosskopf et al. (2006) find that counterfactual information can increase risky behavior, this result disappears with experience, suggesting that subjects become less

[8]Field data suggests that ambiguity is an important factor in market participation. For example, Antoniou et al. (2015) and Dimmock et al. (2016) find that ambiguity has a negative effect on market participation, and Bianchi and Tallon (2018) find weak evidence of a negative effect using french data. Our environment aims to limit ambiguity by providing full information on the data generation process and including a large number of a realizations to facilitate comprehension of the dynamic process. In bandit problems, Meyer and Shi (1995) find that subjects chose less ambiguous arms. Anderson (2012) finds that subjects who are ambiguity averse are willing to pay for information.

[9]Lian et al. (2018) employ MTurk subjects and MBA students and show that, holding the risk premium fixed, low risk-free interest rates lead to higher participation in risky projects.

[10]The experimental design of Biele et al. (2009) employs a Markov process for the risky option, with only two states H and L, which is unknown to the subjects. In our experiment, we enrich the set of possible outcomes while also familiarizing the subjects with the payoff realization process. In a complex task with six restless arms, Payzan-LeNestour and Bossaerts (2014) find evidence that reinforcement learning may explain their findings better than Bayesian updating (unless the subjects are nudged about the regime changes).

sensitive to additional information. Yechiam and Busemeyer (2006) show that counterfactual information can increase risky option selection when the negative outcome is rare and large.

2 Environment

For each $t = \{1 \ldots, T\}$, a player will seek to maximize state (s) dependent utility $u_t^s(\pi)$, by choosing between (i) IN $(a = 1)$ or (ii) OUT $(a = 0)$. The former yields a stochastic payoff $\pi_t = x_t$ driven by an autoregressive process of order one AR(1) as specified in equation (2) where ϵ follows a standard normal distribution, while the latter yields a risk-free payoff $\pi = r_f$, such that

$$\pi_t = \begin{cases} x_t & \text{if} \quad \text{a=1}, \\ r_f & \text{otherwise}, \end{cases} \tag{1}$$

where

$$x_{t+1} = \rho x_t + \sigma \cdot \epsilon_t. \tag{2}$$

Utility u^s is state dependent, and captures the time-varying risk preferences documented by Guiso et al. (2018). When the risky investment pays less than the risk-free option the market is bearish and the subjects are less tolerant of risk. The increased sensitivity to risk leads them to choose the risk-free investment strategy OUT. Thus, beliefs about the one-step ahead value of the risky payoff x_{t+1}, denoted as $F_t x_{t+1}$ drive the subject's decision between IN or OUT, or

$$a = \begin{cases} 1 & \text{if} \quad u^s(F_t x_{t+1}) > u^s(r_f), \\ 0 & \text{otherwise}. \end{cases} \tag{3}$$

Following Landier et al. (2019), we predict that subjects will form expectations $F_t x_{t+1}$ using extrapolative expectations, where subjects overreact to unexpected innovations (Bordalo et al., 2018), and sticky expectations (Coibion and Gorodnichenko, 2015, Bouchaud et al., 2019), where subjects demonstrate inertia in updating expectations. We use a non-recursive specification for the one-step ahead forecast which depends on current and past RE, denoted as $\sum_{k=0}^{n} E_{t-k}x_{t+1}$, as well as the history of x,

$$F_t x_{t+1} = (1-\lambda)\sum_{k=0}^{n} \lambda^k E_{t-k}x_{t+1} + \gamma \sum_{k=0}^{n} \lambda^k (x_{t-k} - E_{t-k-1}x_{t-k}) \cdot \mathbb{1}_{t-k}, \tag{4}$$

where $\lambda \in [0,1]$ is the degree of stickiness, $\gamma > 0$ captures the importance of extrapolative beliefs and $\mathbb{1}_{t-k}$ takes the value of one when either (i) the information about x_{t-k} is public (e.g. index funds), or (ii) the information about x_{t-k} is private (e.g. hedge funds) and the subject selects the risky investment strategy. A player updates her belief of x according to equation (4) and will switch from OUT to IN when she believes that x will yield a higher payoff than the risk-free investment r_f. Figure 1 shows an example of such belief formation using a series of actual x observed by a participant in one of our sessions. For illustration purposes, we also include the value of x even when OUT is selected. The example assumes the following parameter values: $\{\rho, \sigma, T, r_f, \lambda, \gamma, \} = \{.85, 12, 160, -8, .21, .41\}$, where λ and γ are estimates of behavioral expectations parameters reported by Landier et al. (2019).[11]

Hypothesis 1. *The frequency of IN in the public information treatment is higher than in the private information treatment.*

We perform numerical simulations of subject behavior using x_t from our experimental sessions to formulate Hypothesis 1. These predictions are summarized in Table 1. As illustrated in equation (2), we should expect higher participation rates in the public information treatment due to the mean-reversion process that governs the evolution of x. The mean of x, which is equal to zero, is higher than the risk-free payoff of -8. The sticky and extrapolative expectations in Landier et al. (2019) are similar to the behavior predicted for an RE-type

[11] Landier et al. (2019) results are robust to a family of values of $\rho \in \{0, .2, .4, .8, 1\}$, and a value of $\sigma = 20$. Given our tick size, the equivalent standard deviation is $14.142 = 20/\sqrt{2}$ for our design. However, we work with a slightly smaller number, 12, to mitigate fatigue of participants from volatile series. In the user-interface, we also adjust all payoffs by a large constant to avoid negative payoffs.

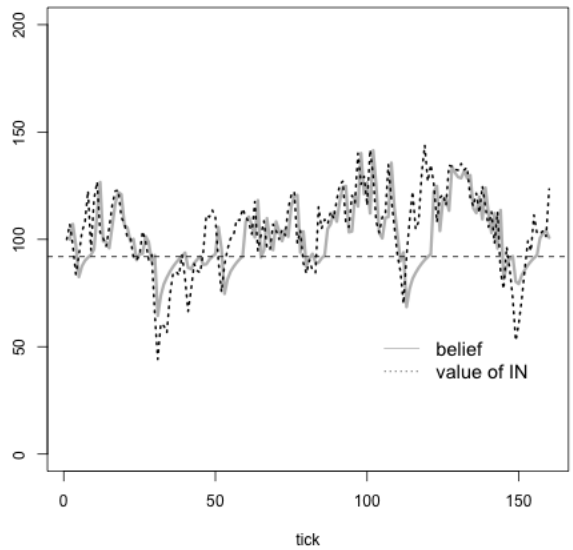

Figure 1: Payoff from choosing IN and the evolution of belief under Landier et al. (2019) model of sticky and extrapolative expectations.

player. Conditional on $x < r_f$, the simulated player should behave similarly under both rules, choosing the risk-free option approximately 70 percent of the time. On the other hand, when $x \geq r_f$ the simulated player will choose the risky investment approximately 88 percent of the time in the public information treatment, and about 75 percent of the time in the private information treatment.

In the second part of Table 1, we calculate the predicted duration of the OUT spells by counting how many ticks a player remains OUT, conditional on being OUT. Simulated player behaviour across treatments is very similar. The median number of ticks is around three, increasing slightly to about five to six ticks at the 75th percentile. A difference in behavior across treatments emerges at 90th percentile, where the number of ticks a player spend OUT is ten to eleven in the public information treatment and six in the private information treatment.

When the risky payoff is below the risk-free payoff, we expect players to switch to the risk-free investment strategy. In the third and fourth sections of Table 1 we present the mean value of x that triggers the switch. On average, simulated players switch at a lower value of

x in the private information treatment. However, when we analyze the first switch, where the information set is comparable across treatments, the switching values of x are similar. Likewise, we also compute the value of x that triggers the decision to switch from OUT to IN. Predictions across both treatments and behavioral rules are similar and close to the mean value of x, despite the fact that in the private information treatment players do not observe the payoff to the risky investment when OUT. The predicted comparative statics in Hypothesis 1 are robust to increasing the risk aversion of subjects.[12]

Table 1: Predictions

	Landier et al. (2019)		*RE*	
	public	*private*	*public*	*private*
Frequency OUT[a]	.32	.40	.31	.40
Freq. OUT $\|x < r_f$ [b]	.72	.70	.70	.69
Freq. IN $\|x \geq r_f$	.88	.76	.89	.75
OUT spell (ticks)[c]				
10th	1	1	1	1
25th	1	1	1	2
Median	3	3	3	3
75th	5	5	6	5
90th	10	6	11	6
x when switching OUT (all)				
Mean	85.44	82.28	83.25	80.87
SD	6.73	9.44	6.37	8.94
x when switching OUT (first)				
Mean	83.96	83.76	81.64	82.25
SD	9.03	8.61	8.39	8.94
x when switching IN				
Mean	100.67	100.04	100.67	100.04
SD	21.59	20.90	21.59	20.90

Notes:
a. Frequency of OUT is computed using a tick count of when OUT strategy is observed.
b. Frequency of OUT conditional on the realized value of x being below the risky-free payoff.
c. An OUT spell is the number of ticks in which the player stays OUT without switching.

Hypothesis 2. *Investors select IN more often in the private information treatment due to informational demand.*

[12] We work with a power utility, u^{α} where $\alpha \in \{.3, .5\}$. For time-varying α, we assume $\alpha = 1$ when the subject is IN, and $\alpha \in \{.3, .5\}$ when subject is OUT.

Higher participation rates in risky investment will be observed in the private information environment compared to the public information when there is a demand for information. In other words, to obtain information on the payoff of x, subjects may (i) delay their decision to switch from IN to OUT and/or (ii) shorten the OUT spells by re-entering prematurely to explore the risky environment. If demand for information is not significant (Karlsson et al., 2009, and Sicherman et al., 2015), then behaviour consistent with Hypothesis 1 will be observed. However, when demand for information exists, we expect a difference in the median duration of the OUT spells across treatments. In such case, players in the public information treatment are willing to stay OUT longer relative to players in the private information because they know the relative payoffs and have nothing to gain from premature switching.

Furthermore, the value of x which triggers the decision to switch from IN to OUT should be higher in the public information treatment where players do not gain anything from delaying the decision to switch. Players in the private information treatment, on the other hand, gain information when they delay the decision to switch. To accurately identify the value of x which triggers switching and separate the effect of demand for information, we focus on the first switching decision of players when the information sets are comparable across treatments.

3 Laboratory procedures

The experiments were conducted at the MonLee laboratory in Monash University using oTree software (Chen et al., 2016). The subjects, who were recruited online via SONA, include undergraduate students across all fields. All participants were assigned to one of the two possible treatments: (i) public information or (ii) private information.[13] We elicited risk attitudes in all sessions, following the protocol of Crosetto and Filippin (2013).[14] After

[13]The instructions for public information treatment can be found here and for the private information treatment here.

[14]To measure risk attitudes, Crosetto and Filippin (2013) ask subjects to decide how many out of 100 boxes they want to collect. Earnings increase linearly with the number of boxes collected. However, if subjects select a box with a bomb inside, then their earnings are zero. In our experiment, risk-neutral expected earnings (50 boxes collected) are \$2. Appendix A presents the individual choices in the risk elicitation task.

reading the instructions, subjects answered four control multiple choice questions.[15] If a subject answered a question incorrectly, then the experimenter privately discussed with the participant the relevant section of the instructions.

Table 2: Overview of sessions

	Public	*Private*
Profit (points per tick)		
Mean	101.16	100.11
SD	17.25	17.85
Profit ($, no show-up fee)		
Mean	10.12	10.01
Show-up fee ($)	10	10
Number of subjects	41	42
Number of sessions	4	4

Notes: Subjects were paid in Australian dollars.

Each session included two practice rounds, followed by 20 paid rounds. The payoff process for the risky asset was updated every half a second, for 80 seconds (160 ticks) per round. In total, 83 subjects participated in the experiment. Forty-one subjects participated in public information treatment, and 42 participated in the private information treatment. Table 2 presents an overview of all laboratory sessions.

Figure 2 shows the user interface in the public information treatment under two different decisions. The left panel of Figure 2 shows the interface as seen by the subjects when they select IN, and the right panel shows the interface when they select OUT. The user interface for the private information treatment is similar to the public information treatment, except that when the player selects OUT, she no longer observes the payoff to IN. The value of IN, $x + 100$, is depicted with a blue line while the value of OUT appears as a horizontal line at the ordinate value of $r_f + 100 = 92$. For each subject, the default initial state is IN. Subjects

[15]We asked subjects to answer the following questions: (i) what is the average payoff of IN?, (ii) if you select OUT, then you accumulate points according to (100, x, 92, 0), (iii) if you switch from OUT to IN, can you switch again and go OUT? (iv) Does the current value of x affect the value of x in the next period?

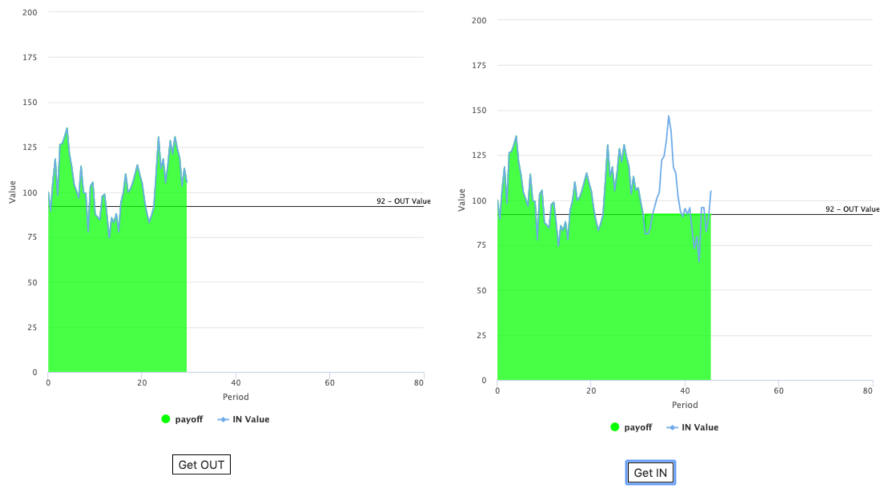

Figure 2: An example of user interface in public information treatment when choosing (a) IN (left panel) and (b) OUT (right panel).

then decide whether to stay IN or switch to OUT by clicking on the button "GET OUT," (or "GET IN" when the current strategy is OUT) located at the bottom of the interface. Players can switch between IN and OUT each tick, which lasts half of a second, for $T-1$ ticks. The green shaded area represents the accumulated payoffs. When a subject selects OUT, the payoffs accumulate at the constant rate of 92 points per tick (see right panel of Figure 2).

At the end of each round, we show the subjects the points accrued over the course of that round as well as the cumulative points earned over all non-practice rounds. The experimental sessions lasted about 50 minutes. The points earned across all rounds were added and converted to cash at the end of the session, at the exchange rate of \$.003125 per 100 points. Excluding the show-up fee of \$10, subjects received on average \$10.12 in the public information treatment and \$10.01 in private information treatment (see Table 2). The similar value of payoffs across the two treatments is due to the mean reversion process that governs the evolution of the value of IN. Despite the similarities in average values, we observe important differences in behavior when the value of x goes below the risk-free payoff, triggering switching of strategies.

4 Results

We begin the analysis of our results using Figure 3, which provides summary statistics for the observed frequency of OUT spells and the duration of the median OUT spell for both treatments. The black bar shows the results for the public information treatment, while the grey bar shows the results for the private information treatment. According to the left panel, subjects stay out of the market more frequently in the public information treatment. The right panel shows that in the public information treatment, the median duration of the OUT spell is longer. However, the overall short nature of median spells (five and three periods) observed in both treatments suggest limited inertia in investment choices.[16]

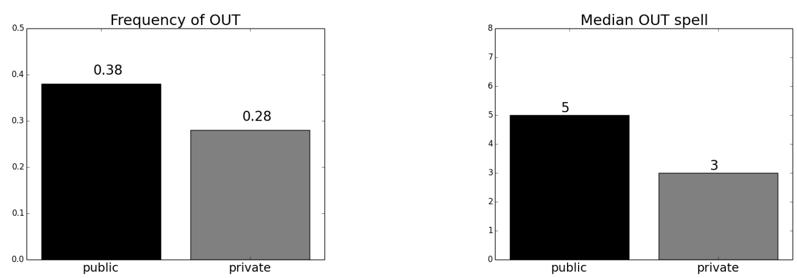

Figure 3: Summary of results

If we look at the information presented in Figure 4, we can see that subjects display a high level of activity in both treatments.[17] The left panel in Figure 4 presents the results for the public information treatment, and the right panel presents the results for the private information treatment. The blue line depicts the value of x, measured against the left y-axis, and the red line depicts the fraction of subjects who choose IN, measured against the right y-axis, at time t. The black line is the risk-free payoff. When the value of IN is high, more players choose the risky strategy, and when the value of IN is low, relatively more players

[16]Field data shows that people with brokerage accounts trade more often relative to other investors, who exhibit inertia in their portfolio choices (Bilias et al., 2010 and Brunnermeier and Nagel, 2008). Using detailed investor portfolio data from Sweden, Calvet et al. (2009) show some evidence of a positive link between wealth changes and risk-taking.

[17]Appendix D has the complete time series observations for all experimental sessions.

choose the risk-free option.

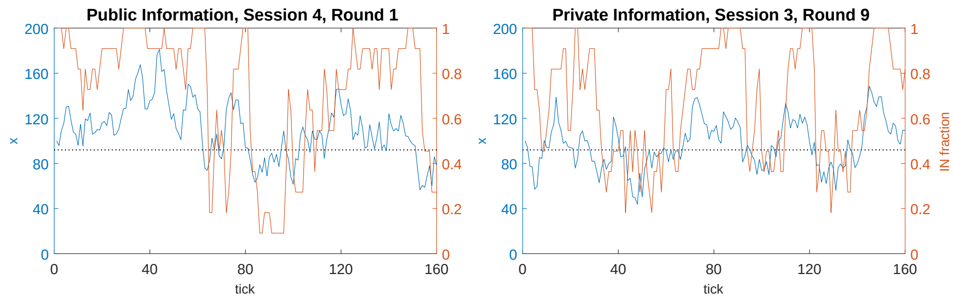

Figure 4: Activity observed in the public (left) and private (right) treatments, depicted by the red line. The blue line shows the value of x at time t, while the black dotted line is the risk-free payoff.

Next we study subject behavior over time in Table 3 using data from (i) all rounds, and (ii) rounds 11 through 20. Summary statistics show that experience does not affect subject behavior. To gain a better understanding subject behavior, we next compute the frequency of OUT conditional on the value of x being below the risk-free payoff (OUT — $x < r_f$), and the frequency of IN conditional on the value of x being equal to or greater than the risk-free payoff (IN — $x \geq r_f$). According to our analysis, subjects play (i) IN 72 percent of the time in the public information treatment and 79 percent of the time in the private information treatment, when that strategy is most profitable, and (ii) OUT 60 percent of the time in public information treatment and 41 percent of the time in private information treatment, when that strategy is most profitable.

The second part of Table 3 presents data on the duration of OUT spells for the 10th, 25th, 50th, 75th, and 90th percentiles. For the upper percentiles, the difference in duration becomes increasingly pronounced. While there is no difference in duration of an OUT spell at 10th and 25th percentiles between the two treatments, at the median, the duration of an OUT spell is two ticks greater in the public information treatment. At the 75th percentile, the duration of an OUT spell in the public information treatment is five ticks greater, increasing to eight ticks at the 90th percentile. Though the difference in the number of ticks increases

Table 3: Summary statistics

	All rounds		*Rounds 11-20*	
	public	*private*	*public*	*private*
Frequency OUT[a]	.38	.28	.40	.29
Obs.	128,000	131,200	64,000	64,000
Freq. OUT $\lvert x < r_f$ [b]	.60	.41	.61	.43
Freq. IN $\lvert x \geq r_f$	.72	.79	.71	.79
OUT spell (ticks)[c]				
10th	1	1	1	1
25th	2	2	2	2
Median	5	3	5	3
75th	11	6	11	6
90th	20	12	22	12
x when switching OUT (all)				
Mean	91.71	88.19	91.58	87.20
SD	17.77	17.64	17.21	17.47
x when switching OUT (first)				
Mean	88.77	85.27	87.50	85.08
SD	17.81	15.41	18.08	15.64
x when switching IN				
Mean	103.96	95.75	103.52	94.51
SD	17.41	20.14	16.96	19.51

Notes:
a. Frequency of OUT is computed using a tick count of when the OUT strategy is observed.
b. Frequency of OUT conditional on the realized value of x being below the risky-free payoff.
c. OUT spell is counted as the number of ticks the entrepreneur stays OUT without switching.

as the percentile increase, the median and the 90th percentile both have the same 5/3 ratio between the public and private information treatments.

In the third part of Table 3 we compute the mean value of x that triggers players to switch from IN to OUT. For the public information treatment, the value is close to the risk-free payoff of 92. For the private information treatment, players wait until x drops to 88 to switch from IN to OUT. If we look at the first switching choice, players switch to OUT at about 88 in the public information treatment and 85 in the private information treatment. The last section of Table 3 presents the value of x that triggers the decision to go back IN. The value is about 104 in the public information treatment. For the private information treatment where the subject does not observe the value of IN, the value is about 96. This is consistent with the shorter OUT duration in the private information treatment, where subjects switch sooner due to lack of information. In the following paragraphs, we formalize our results.

Result 1. *Subjects participate in the risky investment more often in the private information treatment than in the public information treatment.*

The linear probability model in Table 4 confirms that individuals are more likely to select the risky investment in the private information treatment. The dependent variable is the subject investment strategy, IN or OUT, which takes the value of one when the subject is OUT and zero when the subject is IN for all specifications except (IV) where the definition is reversed. Further, in specifications (IV) and (V) the probability is conditional on the value of x. The dummy variable *Private* is the treatment effect and takes the value of one if the subject is in the private information treatment and zero if the player is in the public information treatment. The dummy variable *Round* is the trend effect which controls for learning. We also include the risk elicitation task as a control in some specifications (II), (III), and (V). The regressions show that, on average, the frequency of OUT in the private information treatment is 10 percentage points lower. This coefficient is robust to risk preferences (II-III) and learning (III).

Specification (IV) restricts the sample to when the risky investment outperformed the risk-free investment and specification (V) restricts the sample to when the risky investment under-performed the risk-free investment. The regression in column (IV) confirms that players in the private information treatment are stay IN more often relative to players in the public information treatment. The largest difference in behavior is observed in specification (V) when the sample is restricted to $|x < r_f$, or where the risky investment has a lower payoff than the risk-free investment. In this subsample, the frequency of OUT in the private information treatment is 17 percentage points lower. If information had no value, then players would select OUT more often in the private information treatment (see Table 1). Thus, specification (V) implies that subjects in the private information treatment value information on the payoff of the risky investment, and are willing to stay IN even when it is costly.

To confirm that these results are robust, Table 7 in Appendix B presents the linear regression results for rounds in which the value of IN is below 80 for at least 40 ticks. We conclude that the treatment differences are robust to when players are in markets with a low rate of return.

Table 4: Linear probability model

	(I) OUT	(II) OUT	(III) OUT	(IV) IN $\|x \geq r_f$	(V) OUT $\|x < r_f$
Intercept	$.38^{***}$	$.41^{***}$	$.38^{***}$	$.72^{***}$	$.62^{***}$
	(.02)	(.02)	(.02)	(.01)	(.02)
Private	$-.10^{***}$	$-.10^{***}$	$-.10^{***}$	$.06^{**}$	$-.17^{***}$
	(.01)	(.02)	(.02)	(.02)	(.02)
Round	—	—	$-.00^{***}$	—	—
			(.02)		
Controls (Risk)	No	Yes	Yes	No	Yes
R^2	.01	.01	.01	.01	.03
N	259 200	259 200	259 200	170 359	88 841

Notes: The Intercept captures the public information treatment. Standard errors are in parenthesis, clustered at the subject level and are computed via bootstrapping. $^{***}p \leq .01$, $^{**}p \leq .05$, $^{*}p \leq .1$

Result 2. *Duration of an OUT spell, or an uninterrupted participation in the risk-free investment without switching, is longer in the public information treatment.*

To analyze the duration of an OUT spell, we use a Weibull survival function,

$$S(t; p, z_j\beta) = \exp(-\lambda_j t_j^p),$$

where t is the number of ticks that a player chooses OUT, p is the shape parameter and $\lambda_j = \exp(z_j\beta)$, which includes the regressors (z_j) and the coefficient (β). The hazard rate is computed as

$$h(t) = f(t)/S(t) = -\frac{d \ln S}{dt}.$$

The estimated parameters of the hazard function are presented in Table 5 and the survival function $S(t)$ is shown in Figure 5. The standard errors in the parametric estimation are clustered at the subject level. We find that $p < 1$, which indicates that $h(t)$ is a decreasing function. Note that in each round, we observe multiple *OUT* spells.

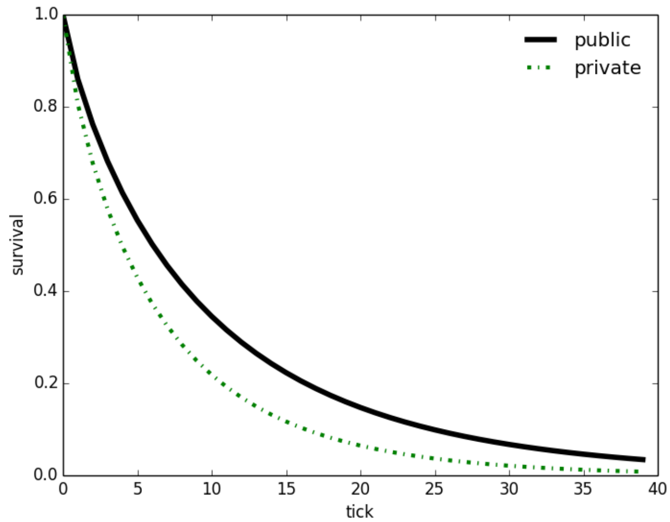

Figure 5: Weibull survival function: $OUT \rightarrow IN$

The survival function confirms that subjects in the public information treatment stay out longer (solid black line) than in private information treatment (dashed green line). We estimate the survival function using the parameters from Table 5 and find that the coefficient for *Private* is .36, or the hazard rate is 1.43 (= exp(.36)) in the private information treatment relative to public information treatment. The hazard rate does not significantly change when we control for risk preferences in specification (II).

Table 5: Hazard function

	(I)	(II)
Intercept	-1.89^{***}	-1.74^{***}
	(.06)	(.08)
Private	$.36^{***}$	$.38^{***}$
	(.14)	(.14)
$\log(p)$	$-.16^{***}$	$-.16^{***}$
	(.03)	(.03)
Control (Risk)	No	Yes
ψ	6.96	8.55
N	86 169	86 169

Notes: To compute the hazard ratios, we use an exp function on relevant coefficients.
$^{***}p \leq .01$, $^{**}p \leq .05$, $^{*}p \leq .1$

The shorter *OUT* spells in the private information treatment indicate that information has value. Subjects choose *IN*, which may be costly, in order to determine and evaluate the payoff of x relative to the risk-free investment. In the public information treatment, on the other hand, subjects know the value of x and can evaluate the relative payoff without switching prematurely. Hence, in the public information treatment, subjects are willing to opt OUT of the risky investment more often.

Result 3. *Subjects wait to abandon the risky investment. They select OUT when the payoff to the risky investment is lower relative to the risk-free investment.*

To determine when subjects switch from IN to OUT, we use a Tobit regression. The decision to switch OUT is dependent on observing a sufficiently low value of x, and therefore, censoring can be an issue which we address by using a Tobit. Since we are interested in a point estimate rather than the duration of an event, a Tobit regression can provide a more precise estimate than a Weibull survival analysis.

Table 6: Switching value of x

	(I) x: $IN \rightarrow OUT$ All	(II) x: $IN \rightarrow OUT$ First	(III) x: $OUT \rightarrow IN$ All
Intercept	90.25^{***}	89.20^{***}	99.71^{***}
	(.99)	(1.36)	(.11)
Private	-3.76^{**}	-3.42^{**}	$-.66^{***}$
	(.91)	(1.65)	(.10)
Controls (Risk)	Yes	Yes	Yes
Pseudo R^2	.001	0.04	.000
N	14 343	1 606	166 791

Notes: All specifications are estimated using a tobit regression. The intercept indicates the value of x in the public information treatment. Standard errors are in parenthesis, clustered at the subject level and are computed via bootstrapping.
$^{***}p \leq .01$, $^{**}p \leq .05$, $^{*}p \leq .1$

Table 6 summarizes the results of the Tobit regressions for the value of x when subjects switch from $IN \rightarrow OUT$ in specifications (I) and (II). Specification (I) analyzes all IN/OUT decisions while specification (II) is restricted to the first IN/OUT switch. In the public information treatment, subjects switch when x is around 90. In the private information treatment, subjects switch when x is about 3.75 points lower. In other words, the subjects in public information treatment do not wait as long to exit (select OUT). This difference can be explained by the fact that in the public information environment, the value of x is always available, and therefore, the payoff to each strategy is clear. This is not the case in the private information treatment, where selecting OUT reduces the information available. Thus, waiting to select OUT suggests that subjects demand information on the relative payoff.

Result 4. *In the public information treatment, when the payoff to the risky investment is above the risk-free alternative, subjects wait to opt IN.*

Specification (III) in Table 6 shows the value of x when subjects switch from $OUT \rightarrow IN$. In the public information treatment subjects wait more to enter when the payoff to the risky investment is higher than the payoff to the risk-free option. When subjects switch, the value of x is close to its mean, as specified in equation (2). In the private information treatment, the subject is uninformed about x and therefore its particular value is not very meaningful because subjects switch in to explore and learn about the relative payoffs. The shorter duration of the OUT spell is consistent with a lower value of x observed in the $OUT \rightarrow IN$ decision.

5 Discussion

In this paper, we study how investor behavior, in our case market participation, varies according to different information disclosure rules. Our experimental results indicate that subjects select the risky investment more often when they need information on the relative payoffs. Thus according to our results, managers could possibly increase profits by selectively disclosing payoff information to those who invest (see Healy and Palepu, 2001 for an overview on reporting and voluntary disclosure). This result is important when considering how disclosure policies affect corporate governance.

In our environment, a mean reversion process governs the returns from the risky investment. There is evidence of mean reversion in intraday trading in index funds, which is a potential application of our model (e.g., see Hasbrouck, 2003). If we were to employ a different stochastic process, then it is possible that participation in the risky market would still be higher under private information, even when the demand for information is not consequential.

Players in our experiment face a situation similar to that of a forecaster who needs to predict when a risky asset will outperform the risk-free alternative (Henriksson and Merton, 1981). Our experiment is an individual decision market timing game. To extend our analysis and better understand how the decisions of others affect investment in risky assets, we need to consider adding social interactions to our design. For example, in related bandit experiments, providing information about the decision of others can help maximize profit (Hanaki et al., 2018) and in an exponential bandit problem, increase free-riding on the information produced by partners (Hoelzemann and Klein, 2018). We leave these ideas for future research.

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Appendix

A. Risk-elicitation results

We elicit risk attitudes following the protocol of Crosetto and Filippin (2013) implemented in oTree (Holzmeister and Pfurtscheller, 2016). The median boxes collected in the public (private) information treatment is 35 (40). Using a Wilcox test, we cannot reject that the distribution of boxes is equal across treatments (p-value of .14). Figure 6 shows the frequency of boxes collected in the two treatments.

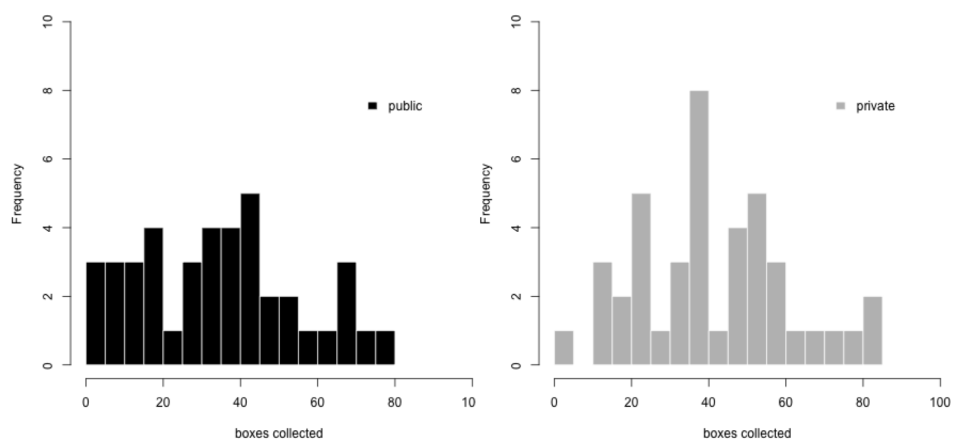

Figure 6: Histogram of boxes collected in the public information (left) and private information treatment (right)

B. Additional robustness checks

In this section, we limit our sample to sessions that experienced low realizations of the risky market. Specifically, we work with rounds in which the value of IN went below 80 for at least 40 ticks (of a total of 160). In this case, we obtain eight (nine) rounds for the public (private) information of a total of 78 (78). We replicate Table 4 using this restricted sample. The results are depicted in Table 7.

Table 7: Linear probability model (restricted sample)

	(I) OUT	(II) OUT	(III) OUT	(IV) IN $\|x \geq r_f$	(V) OUT $\|x < r_f$
Intercept	$.51^{***}$	$.50^{***}$	$.48^{***}$	$.65^{***}$	$.65^{***}$
	(.02)	(.02)	(.03)	(.02)	(.03)
Private	$-.12^{***}$	$-.12^{***}$	$-.13^{***}$	$.08^{***}$	$-.20^{***}$
	(.02)	(.02)	(.02)	(.03)	(.03)
Round	—	—	$-.00^{***}$	—	—
			(.02)		
Controls (Risk)	No	Yes	Yes	No	Yes
R^2	.02	.02	.01	.00	.04
N	28 480	28 480	28 480	14 058	14 422

Notes: The Intercept captures the public information treatment. Standard errors are in parenthesis, clustered at the subject level and are computed via bootstrapping. $^{***}p \leq .01$, $^{**}p \leq .05$, $^{*}p \leq .1$

The treatment differences are consistent with what we observe in the regressions with the full sample (Table 4). The coefficient for *Private* is $-.12$, which confirms that players in the private information treatment chose IN more often compared to the public information treatment. In the public information treatment, as one would expect, players opt for OUT more often in the restricted sample (.51) compared to the full sample (.38).

Furthermore, the performance slightly improves when $x < r_f$ compared to the full sample in the public information treatment. Now, players opt for OUT with a frequency of .65 (compared to .62 in the full sample).

In sum, the main results presented with the full sample are in line with restricting our analysis to rounds in which players experienced a significant number of low realizations for the IN payoff.

C. Logit choice model

In this section, we elaborate on the probabilistic logit choice model to explain the behavior observed in the lab. This seminal discrete choice model, introduced in McFadden (1973) based on the earlier work of Marschak (1959), is widely used to model choice between discrete alternatives. The logit has proven to be an ideal instrument to study stochastic choice in many fields including experimental economics, marketing, transportation economics, demand modelling and labour economics. Popularity of the approach is supported by a simple closed

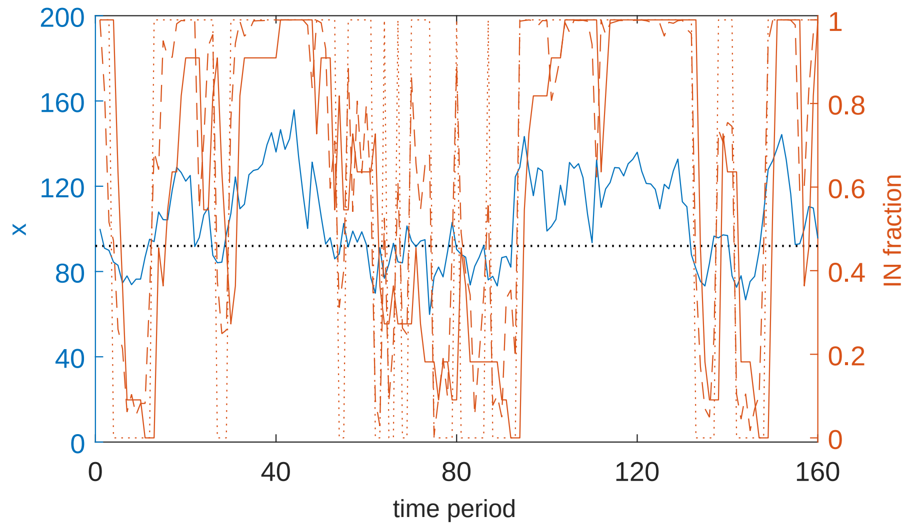

Figure 7: An example of the dynamics observed in the public information treatment Session 3 Round 5 and model predictions: evolution of x (in blue), fraction of subjects being IN (in red), rational choice model predicted fraction of subjects being IN (in red, dotted) and logit model predicted fraction of subjects being IN (in red, dashed) are depicted. Black dotted line is the risk-free payoff.

form specification, strong empirical performance, and micro-foundations based on Random Utility Model (RUM). RUM allows a choice of agent to be governed not only by an observed component of utility —expected payoff— but also by non-observed shocks.

Consider the logit model of choosing IN strategy. The probability of playing IN in period $t+1$, denoted as $P_{t+1,IN}(F_t x_{t+1})$, is a function of (i) the IN expected payoff $F_t x_{t+1}$ and (ii) risk-free payoff r_f,

$$P_{t+1,IN}(F_t x_{t+1}) = \frac{\exp(\beta F_t x_{t+1})}{\exp(\beta F_t x_{t+1}) + \exp(\beta r_f)}, \tag{5}$$

where $\beta \geqslant 0$ is the logit parameter, which represent effects of payoffs on choice probability.

The logit probability represents "noisy" version of the previously considered cut-off strategy.[18]

[18] Allowing a choice decision process to have a stochastic component substantially improves explanatory power of a great number of models. For example, sharp predictions of Nash Equilibrium often fail to be

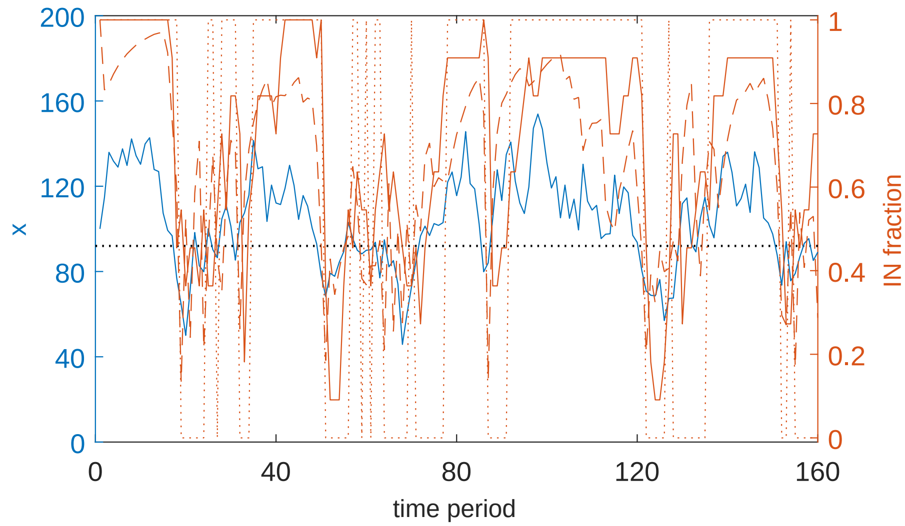

Figure 8: An example of the dynamics observed in the private information treatment Session 4 Round 6 and model predictions: evolution of x (in blue), fraction of subjects being IN (in red), rational choice model predicted fraction of subjects being IN (in red, dotted) and logit model predicted fraction of subjects being IN (in red, dashed) are depicted. Black dotted line is the risk-free payoff.

Market participant still makes the decision to choose IN or OUT strategy based on expected payoffs of corresponding strategies, and for $\beta > 0$ chooses the more profitable strategy with higher probability. At the same time, the model allows that the players to choose an inferior option with a positive probability. This feature of having non-binary decision outcome adds flexibility which is needed to explain subjects' switches between IN and OUT strategies. How responsive is an agent to payoffs and how close the probability of play is to either zero or one depend on the parameter β. For $\beta = 0$ agent ignores information on payoffs and choose strategies with an equal probability. As β increases choices become less noisy, approaching best-responses with $\beta = \infty$. Figure 7 and Figure 8 demonstrate relative fitness of rational and logit choice models in public and private information treatments respectively.

We use data on fractions of subjects choosing strategy IN at period t, denoted by $n_{t,IN}$,

replicated in laboratory experiments, while its "noisy" version —Quantal Response Equilibrium— became a benchmark in experimental economics due to its power in explaining experimental data, see Palfrey et al. (2016) for details.

to fit the logit model (5). We pool the group data for all periods and sessions per treatment. For each treatment we modify model (5) in accordance with the available information. In the public information treatment, all participants have access to the complete history of both IN and OUT options payoffs. As a result they share the same beliefs over profitability of option IN ($E_t x_{t+1}$) regardless of their current and past choices. Therefore model prediction over the fraction of those who choose IN in period t $P_{t,IN}(E_{t-1}x_t)$ takes the following simple form:

$$P_{t,IN}(x_{t-1}) = \frac{\exp(\beta E_{t-1}x_t)}{\exp(\beta E_{t-1}x_t) + \exp(\beta r_f)}. \tag{6}$$

In the *private* information treatment, for those who choose OUT, beliefs evolve according to RE. Moreover, at each tick t beliefs depend on the last observed payoff of IN, demonstrating strong history dependence. For estimation purposes we create 160 cohorts (indexed by j) —total number of ticks— which share the last observed IN payoff (RE expectation E_j is formed based on x_j) and beliefs (specified for every tick t as $E_j x_t$). Denote by $E_j x_t$ the expectation over value x_t which was made at period t that is based on observation of x_j —a last observation of x for those subjects from cohort j who switched OUT in period j and did not switch back to IN. Every period a portion of those who switched OUT in each cohort will switch to IN. In this case we can recursively define a fraction of subjects choosing IN strategy $N_{t,IN}$ as a function of previous number $N_{t-1,IN}$ and a fraction of those who decided to switch IN from every previous cohort j of those who switched OUT after observing x_j. Set $N_{1,IN} = 1$, then fraction evolves as follows:

$$N_{t,IN} = N_{t-1,IN}P_{t,IN}(x_{t-1}) + \sum_{j=2}^{t-1}\Big(N_{j,IN}\big(\prod_{s=j+1}^{t-1}(1 - P_{s,IN}(E_j x_s)\big)P_{t,IN}(E_j x_t)\Big). \tag{7}$$

Models are fitted using quasi-maximum likelihood method by performing a grid search for parameter values which would minimize Mean Square Error (MSE) of one-period ahead prediction of the model for observed $n_{t,IN}$.[19] We further consider expected payoffs that evolve according to rational expectations. In case of *public* information treatment the MSE

[19] This approach was previously used to fit the β parameter to the data in, for example, Anufriev and Hommes (2012).

is defined as follows:

$$MSE(\beta) = \sum_{i=1}^{N} \sum_{t=2}^{T} (n_{i,t,IN} - P_{i,t,IN}(\beta))^2, \tag{8}$$

where $i = 1 \ldots N$ is an index of experimental session in a treatment, $t = 2 \ldots T$ is an index of a tick in a session, and $P_{i,t,IN}(\beta)$ is a standard logit model prediction with slightly modified notation to stress the dependence of prediction on the parameter β.

Table 8: Estimated models of choice

	Rational	Standard logit		Logit with risk aversion		
	MSE	β	MSE	β	α	MSE
Private	2365.00	.20	896.21	.22	.001	899.25
Public	2006.56	.07	837.14	.08	.002	837.26

Notes: Parameters are estimated by grid search minimizing Mean Square Error (MSE) reported.

We further extend our analysis of choices to allow subjects utility function to exhibit different level of risk aversion. We consider exponential utility function which implies constant absolute risk aversion (CARA), denoted by α. Utility is transformed as follows:

$$u(\pi) = (1 - \exp(-\alpha\pi))/\alpha, \tag{9}$$

where π denotes expected payoff.

We use this utility function to fit two-parameter (β, α) logit model of choice.[20]

Table 8 contains estimated results for three different models: benchmark rational choice model, a logit model and a logit with risk aversion. By examining values of MSE we can clearly see that benchmark rational model is inferior to the logit model of choice. At the same time allowing for a risk aversion does not add to explanatory power and gives nearly risk-neutral estimates.

[20]Additionally, we allow for state-dependent risk aversion: we introduce two separate CARA coefficients. One coefficient for those who are making choice while being IN, and one for those who is choosing while being OUT. Results are similar to non-state dependent risk aversion parameter with one exception–for this model participants who are OUT in private information treatment have positive estimate of risk-aversion parameter (that is demonstrate risk-seeking behavior). This is in line with high participation rates in private information treatment which can be explained by risk seeking behavior of subjects with limited information.

D. Plots of sessions. (For Online publication)

Here, we present more examples and collect dynamics from all sessions of both treatments. We provide graphs of the fraction of players choosing IN in the experiment and evolution of IN option payoffs.

Treatment ***public*** information

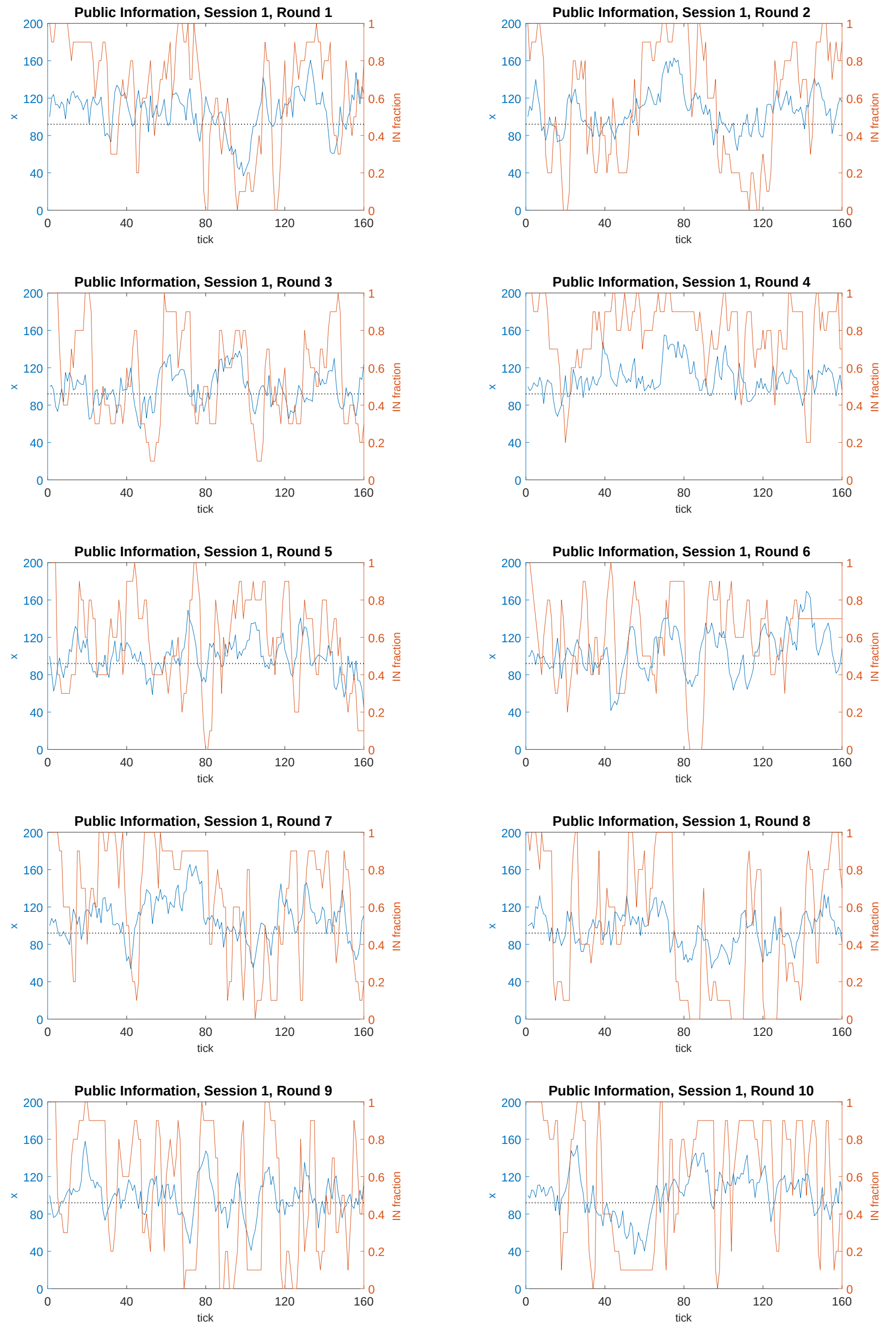

Figure 9: Time series of choices and x_t (public) - Session 1 Round 1-10

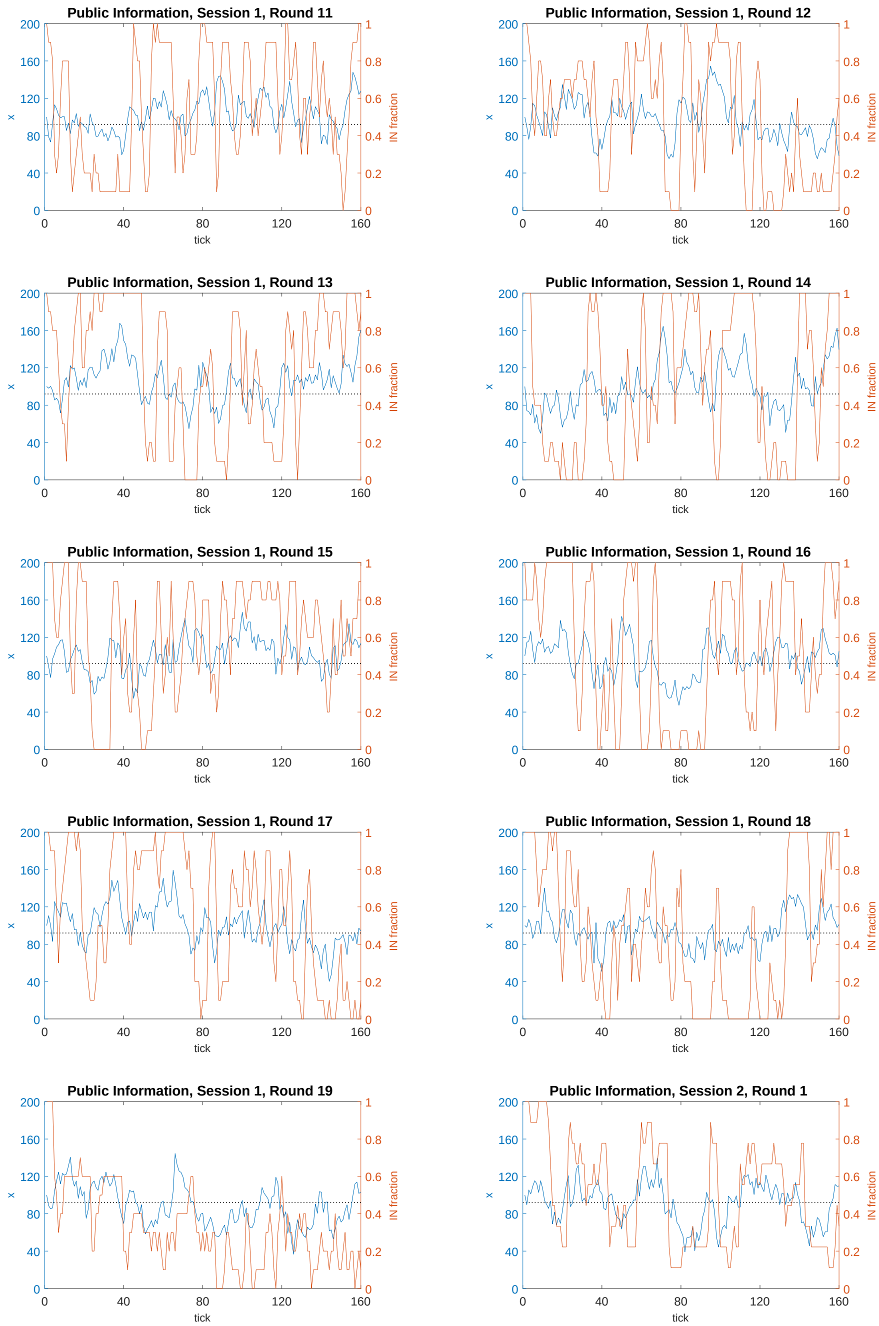

Figure 10: Time series of choices and x_t (public) - Session 1 Round 11-20, Session 2 Round 1

Figure 11: Time series of choices and x_t (public) - Session 2 Round 2-11

Figure 12: Time series of choices and x_t (public) - Session 2 Round 12-20 and Session 3 Round 1

Figure 13: Time series of choices and x_t (public) - Session 3 Round 2-11

Figure 14: Time series of choices and x_t (public) - Session 3 Round 12-20, Session 4 Round 1

Figure 15: Time series of choices and x_t (public) - Session 4 Round 2-11

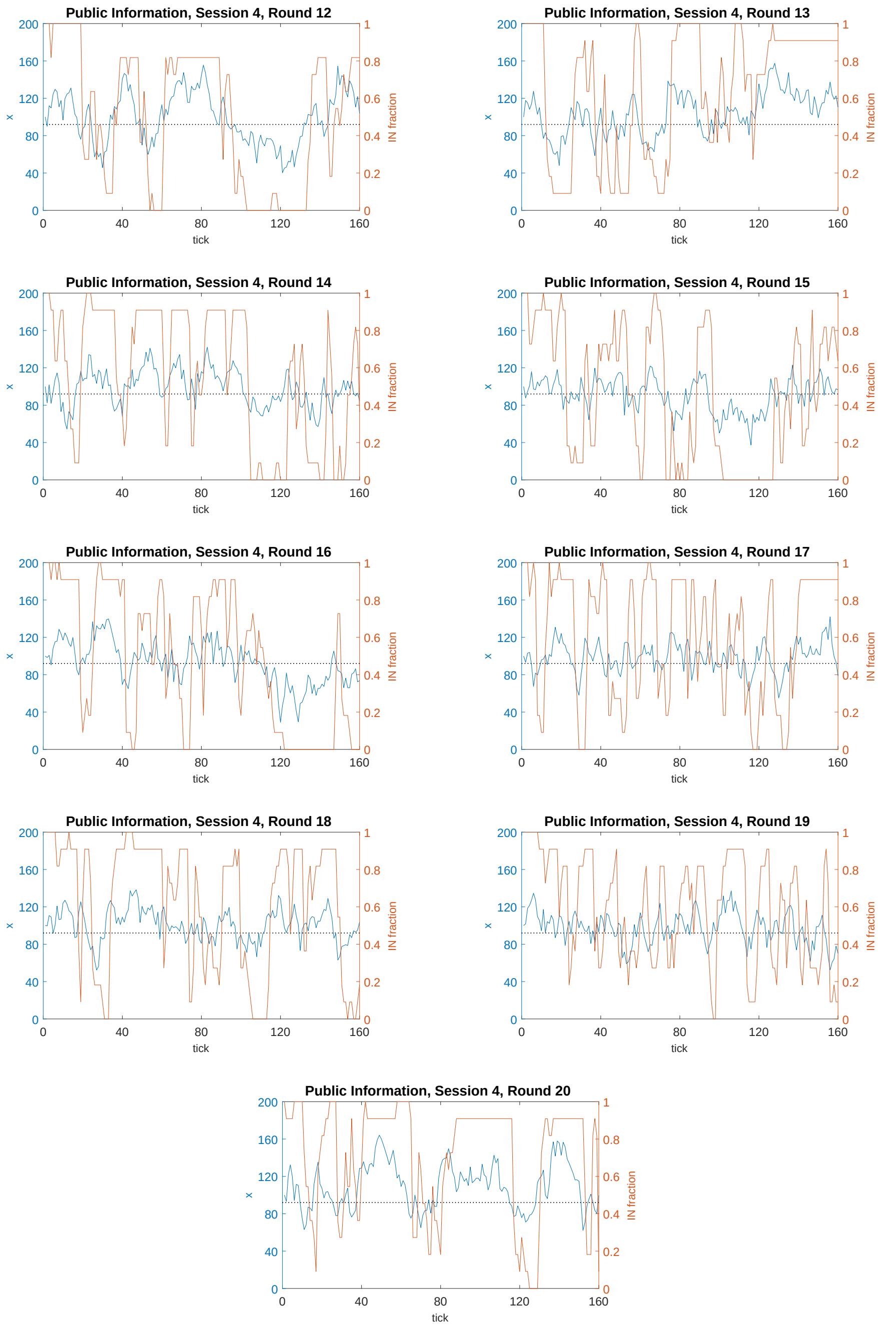

Figure 16: Time series of choices and x_t (public) - Session 4 Round 12-20

Treatment *private* information

Figure 17: Time series of choices and x_t (private) - Session 1 Round 1-10

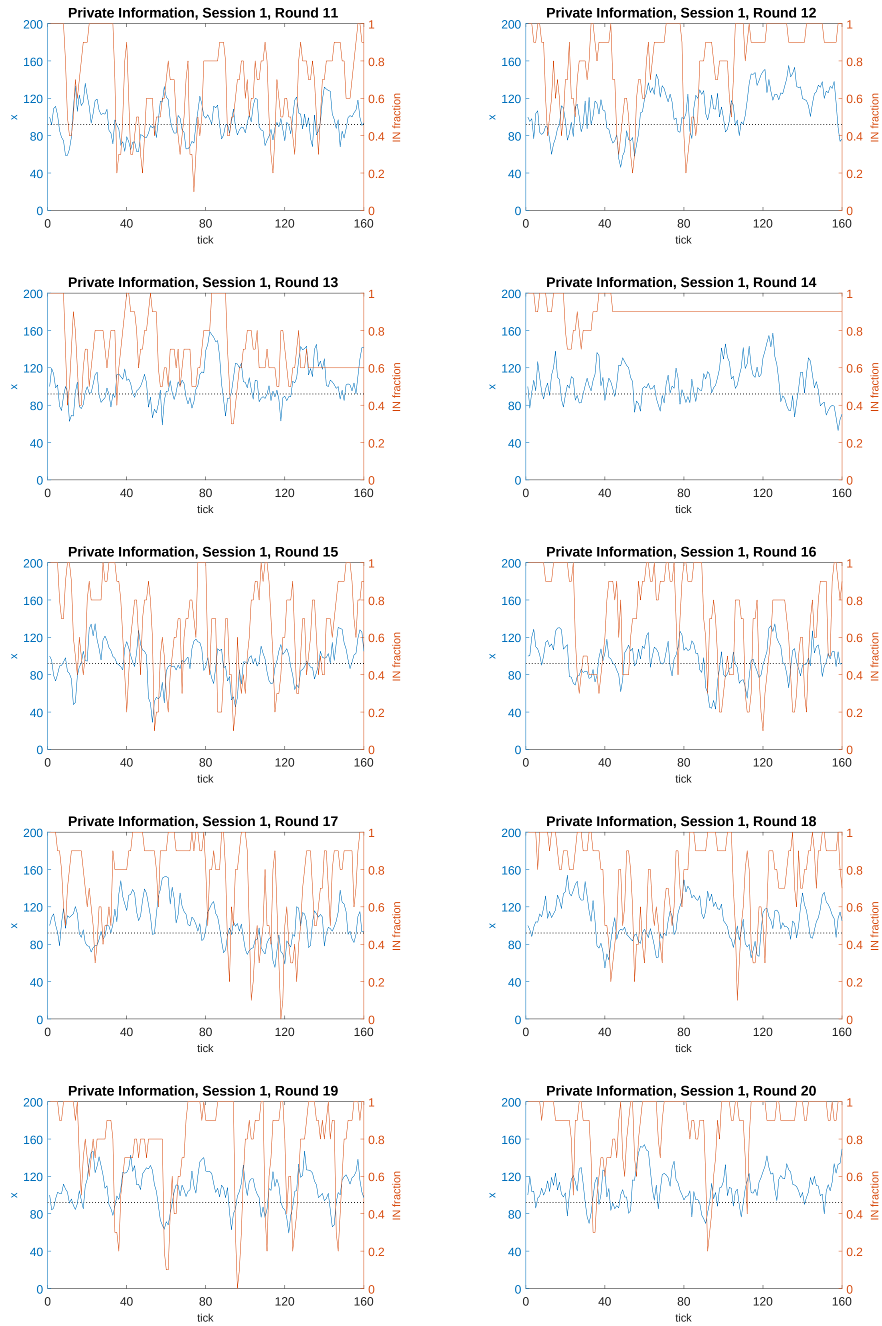

Figure 18: Time series of choices and x_t (private) - Session 1 Round 11-20

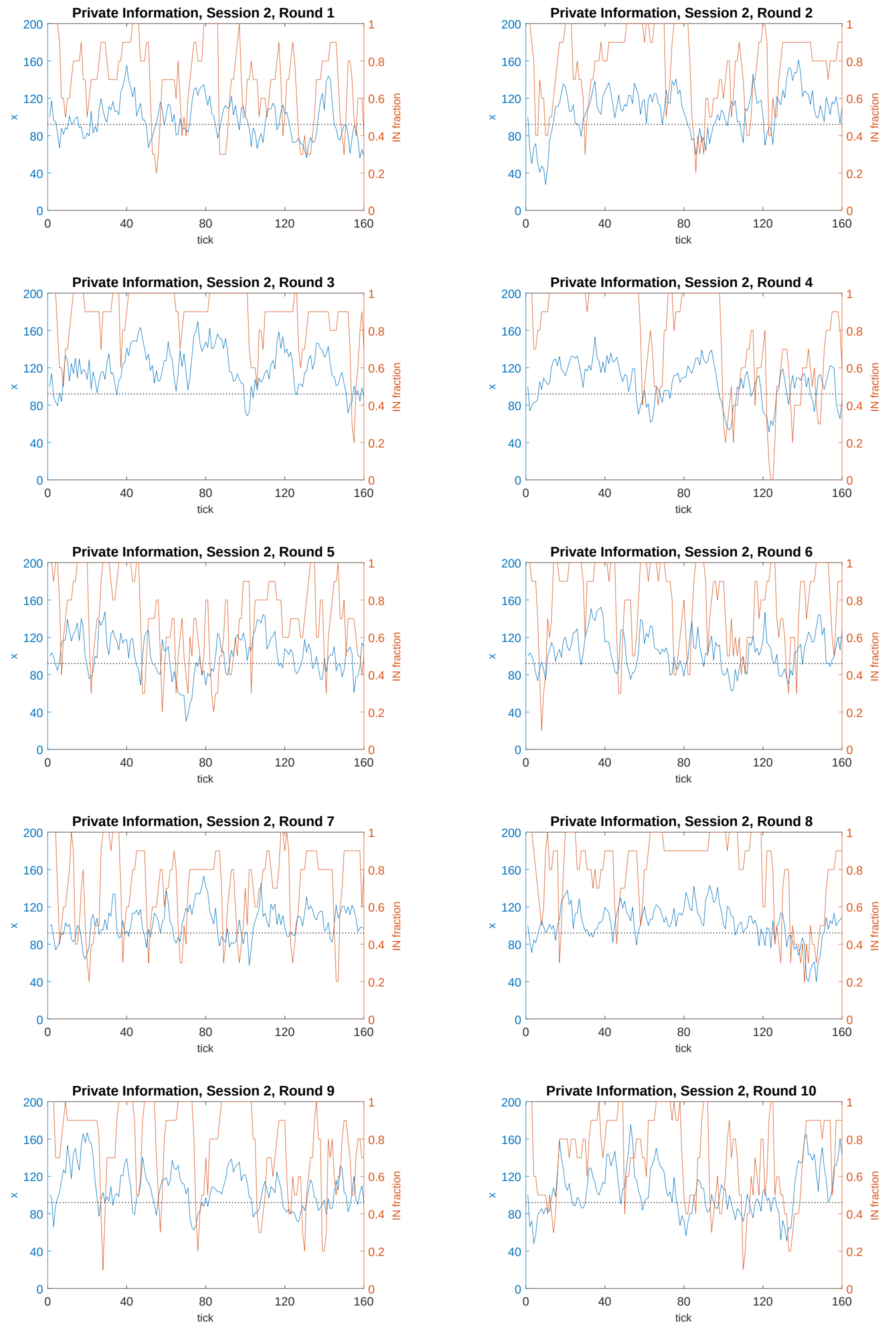

Figure 19: Time series of choices and x_t (private) - Session 1 Round 11-20

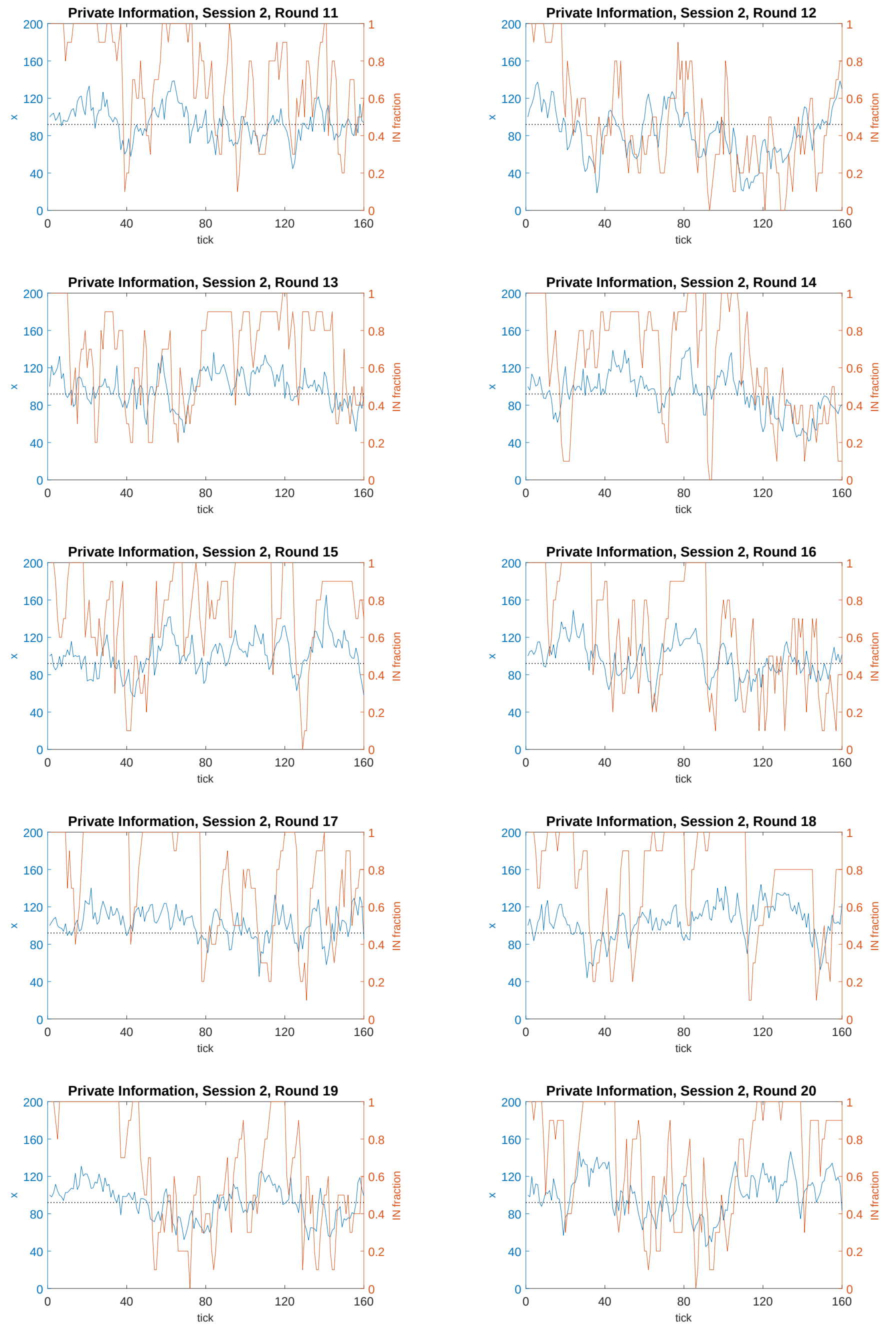

Figure 20: Time series of choices and x_t (private) - Session 2 Round 11-20

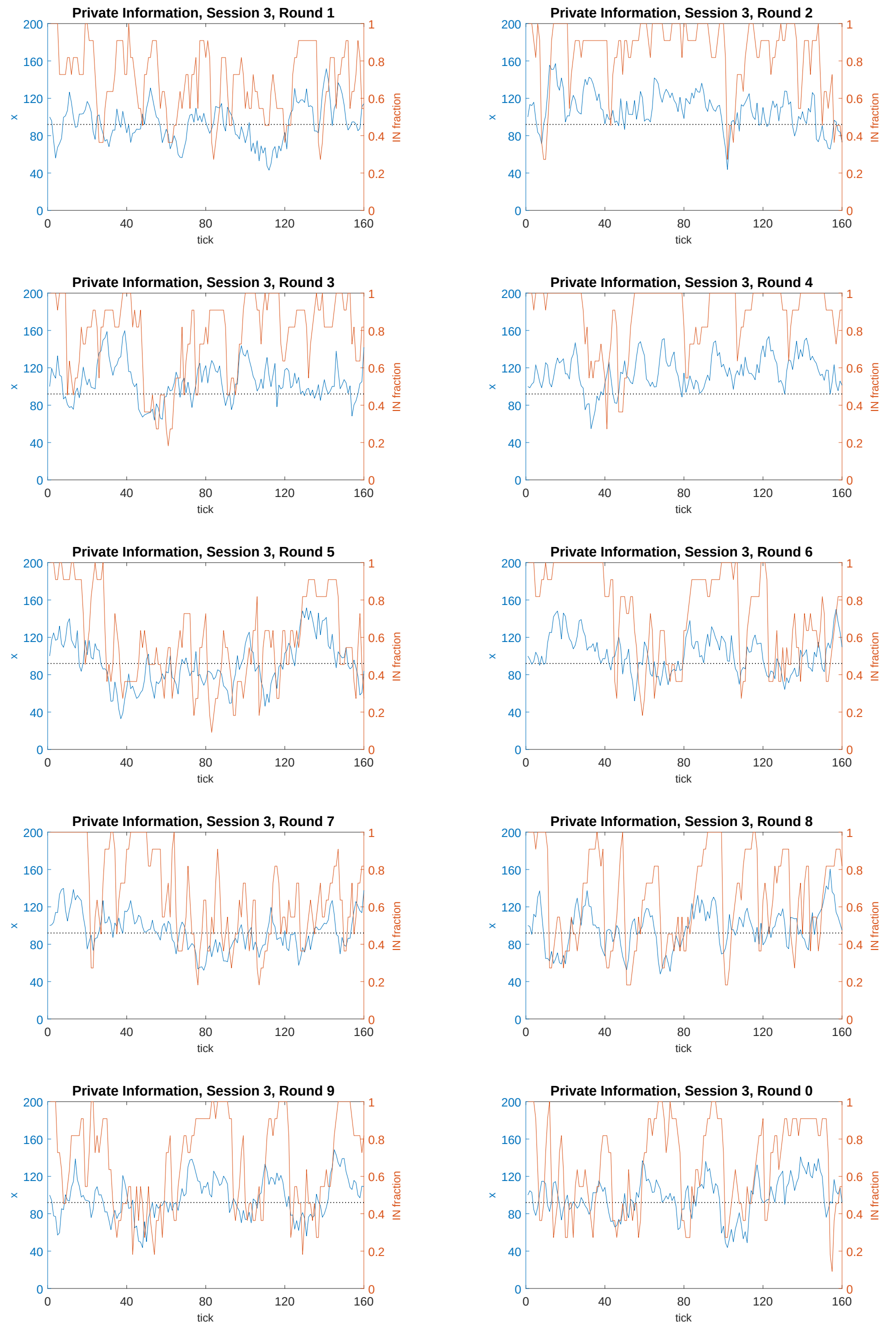

Figure 21: Time series of choices and x_t (private) - Session 3 Round 1-10

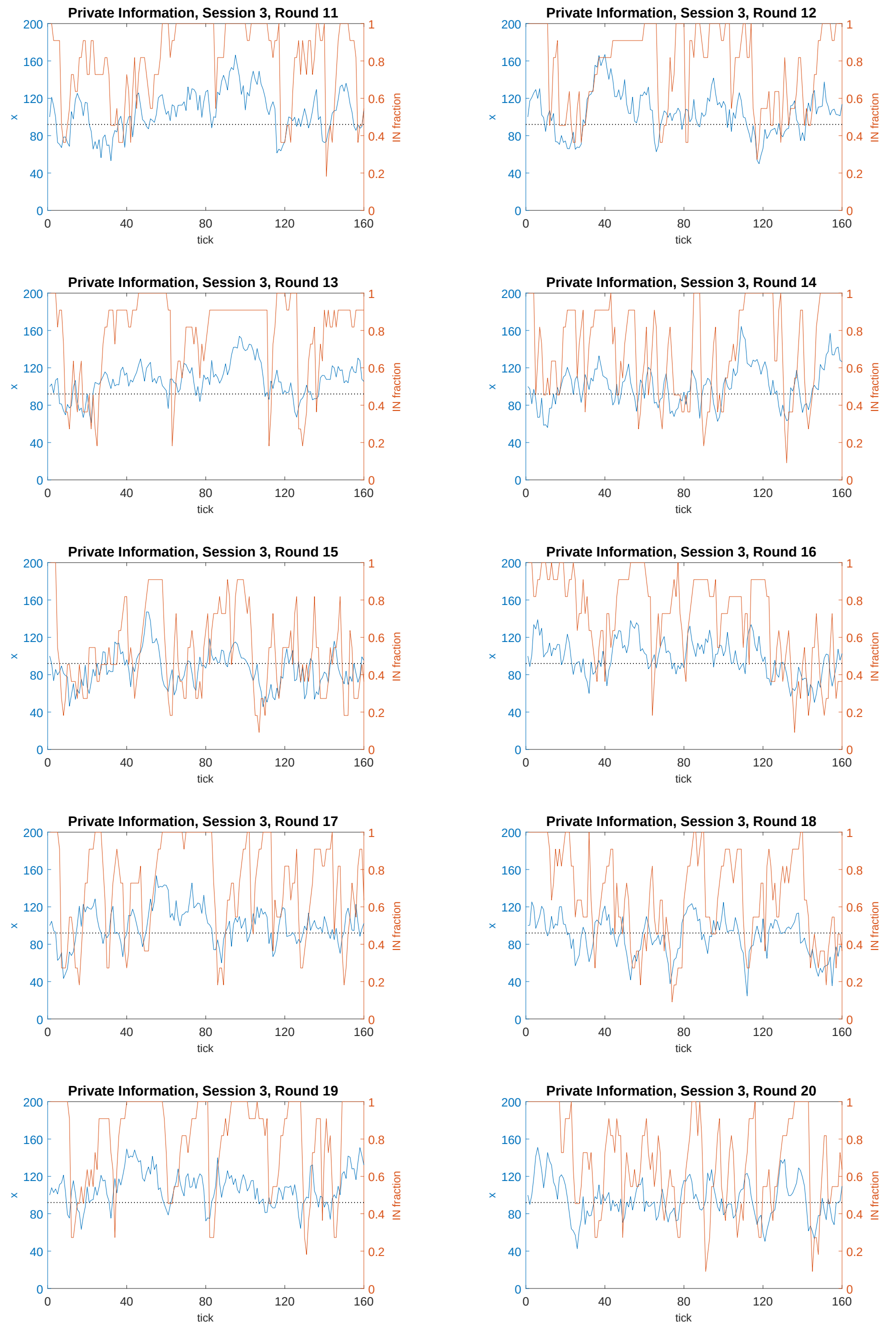

Figure 22: Time series of choices and x_t (private) - Session 3 Round 11-20

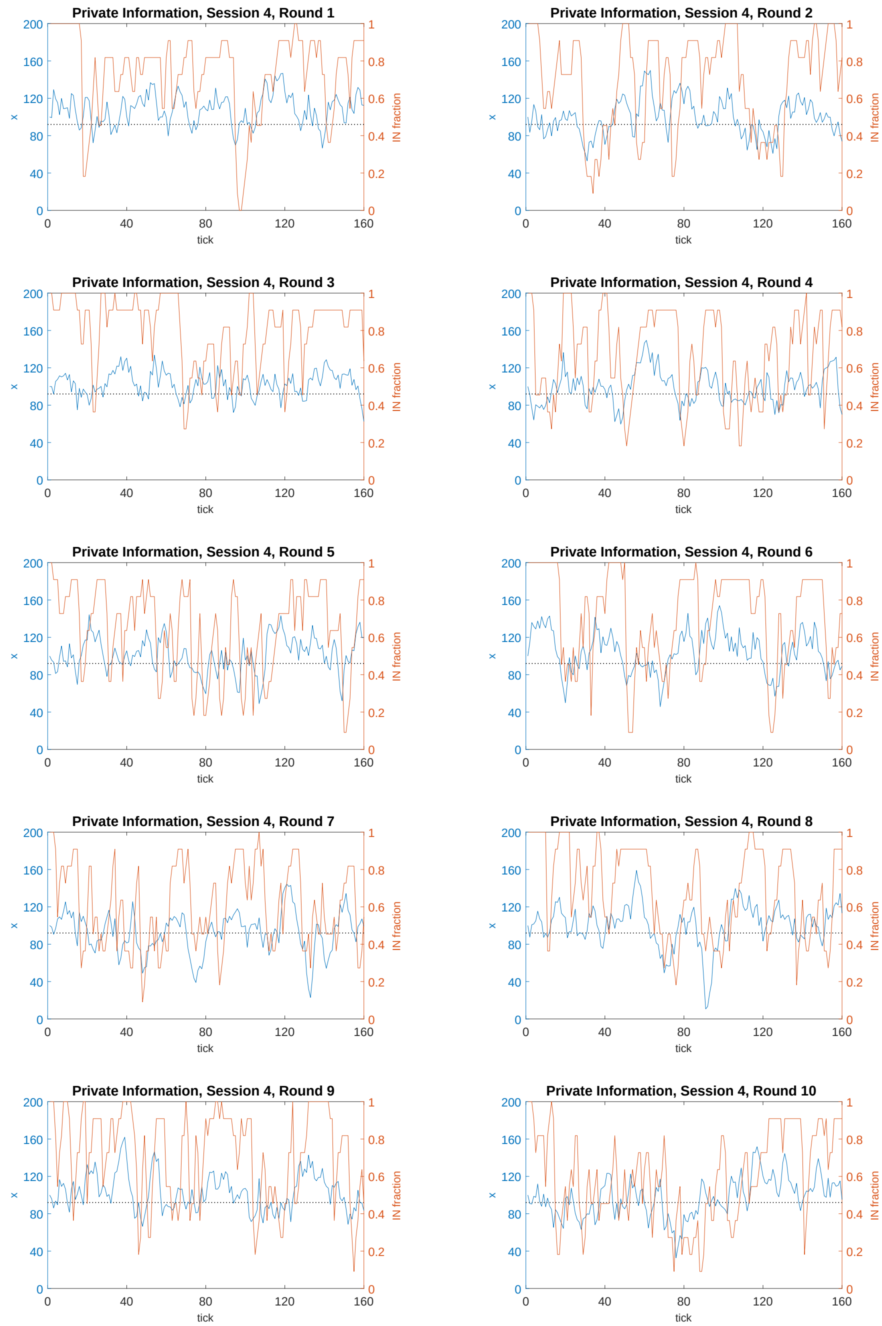

Figure 23: Time series of choices and x_t (private) - Session 4 Round 1-10

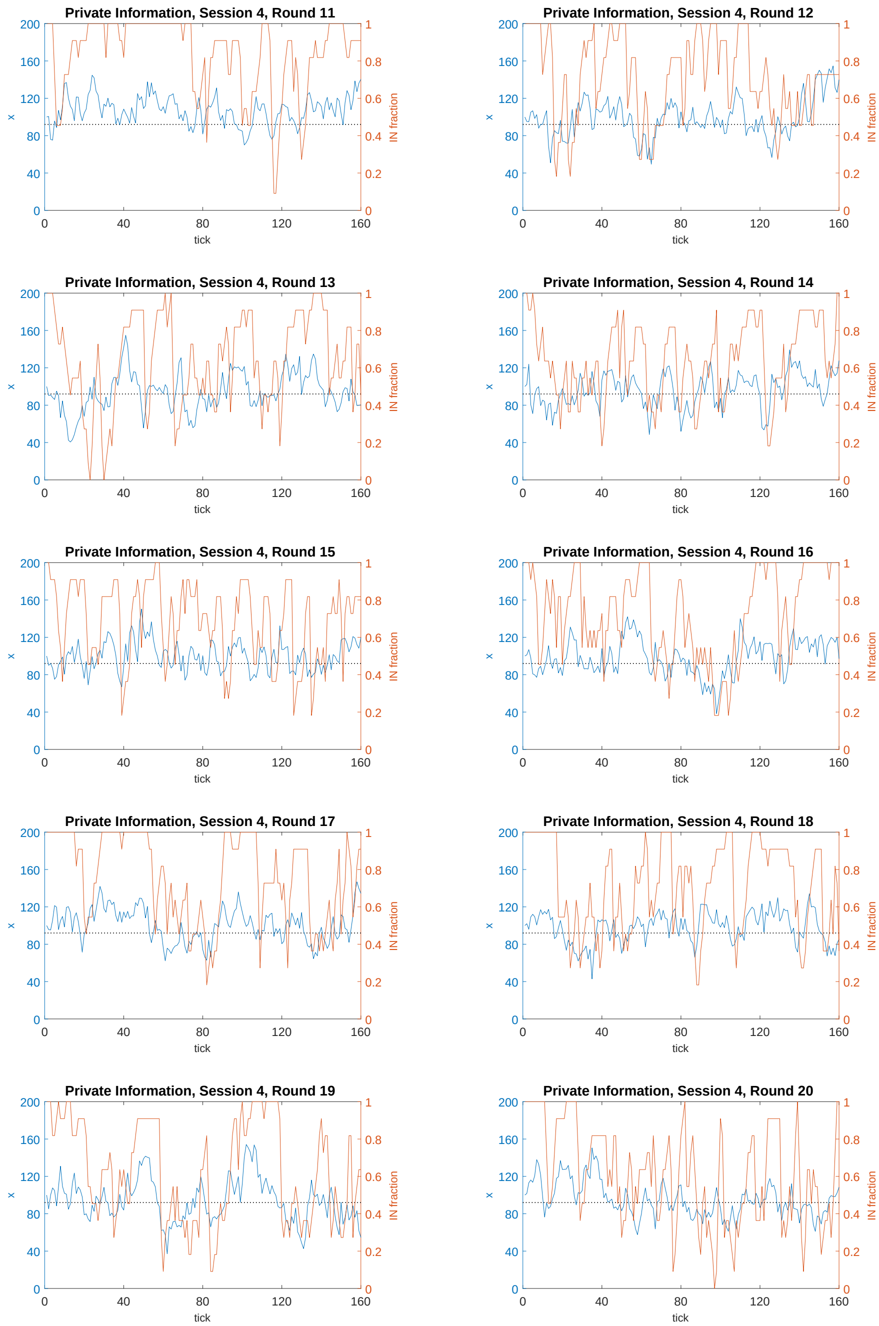

Figure 24: Time series of choices and x_t (private) - Session 4 Round 11-20