Is response time predictive of choice? An experimental study of threshold strategies[*]

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Abstract

This paper investigates the usefulness of non-choice data, namely response times, as a predictor of threshold behavior in a simple global game experiment. Our results indicate that the signals associated to the highest or second highest response time at the beginning of the experiment are both unbiased estimates of the threshold employed by subjects at the end of the experiment. This predictive ability is lost when we move to the third or higher response times. Moreover, the response time predictions are better than the equilibrium predictions of the game. They are also robust, in the sense that they characterize behavior in an "out-of-treatment" exercise where we use the strategy method to elicit thresholds.

Keywords*: Response time, threshold strategies, global games.*

JEL codes: C71, C9, D03, D89.

1 Introduction

There is a long tradition in psychology and neuroscience of using non-standard (non-choice) data to explain the process of choice. In these studies investigators look for neuro correlates inside the brain to explain observed choices in an attempt to find a link between what people do and what they think. The exercise in many of these papers is to correlate observed behavior to neuro correlates with the arrow pointing from observable behavior to the brain.[1] In this paper we reverse this procedure and use internal brain processes to make point predictions about future choices. In particular, we use Response Time (RT) to predict observed thresholds in a global games experiment. Global games are binary action games with incomplete information where payoffs are determined by a state variable that is not known to agents. Instead, agents observe noisy private signals about the state variable and payoffs are determined in such a way that they find it optimal to take one action for realizations of their signal above some critical threshold, and another action for realizations below it. We define a subject's RT as the time that expires between when the subject first observes his signal and when he makes his binary choice. We can think of this as a subject's contemplation time.

Our results suggest that by looking at observations associated to the highest or second highest RT at the beginning of the experiment (first 25 rounds) we can predict observed thresholds (albeit

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[1]Such a process is counter to the typical revealed preference methods used by economists (see Gul and Pesendorfer, 2008).

not necessarily equilibrium thresholds) at the end of the experiment (last 25 rounds). In particular, the signals associated to the highest or second highest RT during the first 25 rounds of the experiment furnish estimates of observable thresholds at the end of the experiment that are both unbiased and comparable to those that could be made using the observable choices of subjects in the first half of the experiment.

Our aim in this paper is exploratory, in the sense that we are interested in discovering whether RTs can predict observed choices, whether there exists any interesting heterogeneity of types in the population that exhibit different RT patterns, and finally whether other existing models of RT (mainly formulated for single-agent choice situations) are useful in explaining our data.

In pursuing this agenda we use our RT results to characterize two types of subjects whom we call Intuitionists (or Discoverers) and Learners. Intuitionists seem to have an intuition about the use of a threshold strategy and even its precise value from the beginning of the experiment, but simply can't articulate what it is. Hence, when offered a signal that is below their threshold they quickly take one action and when offered one above it they quickly take the other action. However, when a signal close to their true threshold is received for the first time, Intuitionists spend a longer time contemplating it since it is not necessarily clear which action to take.

Learners, on the other hand, act as if they understand the structure of the game, and maybe even the benefits of a threshold strategy, but do not know the appropriate threshold to use. They learn their threshold through experience in the game and trial and error. As a result, Learners are more prone to make mistakes in initial rounds, in the sense that in early rounds they violate the dictates of their eventual future threshold. Once they converge on a threshold, however, their behavior becomes indistinguishable from that of Intuitionists.[2]

To support our findings, we present an "out-of-treatment" exercise where we analyze the results of a second experimental treatment where subjects play a global game but we use the strategy method and explicitly ask subjects to report thresholds to be able to observe their evolution over time. We find support for our characterization of Intuitionists and Learners by classifying 80% of the subjects in either one of these two groups.

This paper is by no means the first to use response times in economics.[3] For example, starting in 2006 and using a unique web site where a huge number of responses can be registered to play any listed game or decision problem, Ariel Rubinstein has been an early and persuasive advocate of the use of RTs.[4] For example, Rubinstein (2007) suggests that not all strategic choices are equivalent in the sense that some are "intuitive" and respond to some salient features of the games being played, some are "cognitive" and require more serious thought, while others are "reasonless" and appear random. What is interesting is that these differences can be seen in the RTs of the subjects with more cognitive choices taking more time to decide. In other words, those choices which by inspection of the game appear to be more sophisticated, when chosen, are the same choices that

[2]The distinction between Intuitionists and Learners that we are making is not very different from what happens when we ask two different people who was the director of a film. While one person may know the answer but is not able to recall it (it is "on the tip of my tongue"), the other may never have known it. If you mentioned names to the first type (the Intuitionist) she would be easily able to reject wrong answers because she would know the right answer when she hears it. The second type (the Learner) would have to go through a very different process and perhaps need to do a search of each name mentioned, since they know they never knew the answer. Similarly, we can think of the distinction between these two types of decision makers as representing agents, one of whom functions using "System 1" and the other "System 2" (see Kahneman, 2011, and Dijksterhuis and Nordgren, 2006), since one agent is processing the experimental task in a quick -unconscious- manner by simply trying to recall what threshold value his intuition provided him, while the other is being deliberate and exerting conscious cognitive energy to learn the correct value.

[3]See Spiliopoulos and Ortmann (2014) for a discussion on the usefulness of RT in experimental economics.

[4]http://gametheory.tau.ac.il

are associated with longer decision times.

In Rubinstein (2008) RTs are used to separate subjects into fast and slow types and look to see how their decisions correlate across different decision problems. Again, the information provided by RTs is valuable in understanding the types of decision makers distributed throughout the population. Finally, in Rubinstein (2013) RTs are used to evaluate when a mistake has been made in a particular decision problem with the signature that mistakes involve lower RTs. Again, these results present evidence about the decision process that is hard to obtain by only observing choice data.

Other papers in the economics literature that use RT are Piovesan and Wengstrom (2009), who find a relationship between egoistic choice and RT in a dictator game where higher RTs are correlated to fairer outcomes, and Wilcox (1993), who measures RT as a proxy for decision cost in the laboratory to study the relationship between decision cost and incentives in environments with different levels of risk.

Our study differs from these papers since we study RT in order to make point predictions of choices, as opposed to correlating RTs to observed choices. In a similar spirit to our study, Chabris et al (2009) study the allocation of time in individual decision making to elicit time preferences and find an inverse relationship between average RT and the difference in expected value between the payoffs associated to each of the possible choices. They find support to the optimization theory of Gabaix and Laibson (2005) and Gabaix et al (2006) which predicts that agents will allocate more time to choices between options of similar expected utility than to choices between options of dissimilar utilities. However, Chabris et al (2009) do not use RTs to make point predictions about choices. One paper that is close to ours in focus is Arkady and Krabijich (2016) who look at response time to study indifference in preferences and who uses this indifference point to estimate parameters in a subject's utility function.

Another advocate of the use of response times to study choice is Antonio Rangel and those working in the Rangel Lab at Caltech. In these studies, the focus of RTs is as an output of the Drift Diffusion Model (DDM), a model that has a long history in the neuroscience literature (see Ratcliff, 1978, and Ratcliff and McKoon, 2008). For example, in a recent paper Clithero and Rangel (2013) compare the predictions of a DDM that combines RT and choice data to the predictions of a logistic model of individual decision making and find support for the DDM approach. This paper is similar in spirit to our paper, but differs in two main respects. One is that the task in Clithero and Rangel (2013) is an individual decision task (choosing between two food alternatives), while our paper studies a strategic environment. Second, Clithero and Rangel (2013) use RTs in combination with choice data to make predictions of future choices, while we use only observations related to RT to make our predictions.

After presenting our results we explore the predictions in terms of RT of three alternative models for our experiment: the Drift Diffusion Model of Ratcliff (1978) and Ratcliff and McKoon (2008), the Directed Cognition Model of Gabaix and Laibson (2005) and Gabaix et al (2006), and the predictions in terms of RT that would emerge from the canonical global games model that we present in section 2. We find mixed support for these models.

The paper is structured as follows. In section 2 we present the model of global games used in the experiment. The experimental design is explained in section 3 and our results are presented in section 4. We discuss three alternative models in section 5 and section 6 concludes.

2 The global game

We use global games as our vehicle to investigate RT since the unique equilibrium in these games takes the form of a threshold strategy, which is easy for subjects to understand and execute in the lab. As we will see, signals close to the individual thresholds are harder to evaluate than those further away, and hence RTs should be reliable indicators of where individual thresholds lie.

A global game, as introduced by Carlsson and van Damme (1993), is a coordination game with incomplete information where payoffs depend on an unknown parameter θ, which we call the state of the world, and on the actions of other players. Global games have been applied to a variety of economic situations such as currency crises, investment decisions, or political revolts.[5]

In this game there are two agents in the economy who have to decide whether to take action A or action B. Action B is a safe action and yields a payoff of zero in all states of the world. Action A is a risky action and taking this action has a cost of T. The payoff from choosing action A depends on the state of the world, θ, and on the actions of the other player. In particular, we can distinguish three different regions for the state θ that will determine how (and if) the action of the other player affects individual payoffs:[6]

- If $\theta \leq \underline{\theta}$, then action B dominates action A, regardless of the action of the other player:

$\theta \leq \underline{\theta}$	A	B
A	$-T, -T$	$-T, 0$
B	$0, -T$	$0, 0$

- If $\theta \in (\underline{\theta}, \overline{\theta})$, we are in the "coordination region" where action A yields a payoff of $\theta - T$ only if both players coordinate on this action. When only one of the players takes action A, his payoff is $-T$:

$\theta \in \left(\underline{\theta}, \overline{\theta}\right)$	A	B
A	$\theta - T, \theta - T$	$-T, 0$
B	$0, -T$	$0, 0$

- If $\theta \geq \overline{\theta}$, action A dominates action B, irrespective of the other player's action:

$\theta \geq \overline{\theta} > T$	A	B
A	$\theta - T, \theta - T$	$\theta - T, 0$
B	$0, \theta - T$	$0, 0$

In this game, however, players cannot observe the true value of θ, instead they receive noisy private signals about it. In particular, they know that θ is randomly drawn from a normal distribution with mean μ_θ and standard deviation of σ_θ, i.e.,

$$\theta \sim N\left(\mu_\theta, \sigma_\theta^2\right)$$

[5] See Morris and Shin (2003) for an overview on global games.

[6] In general, $\overline{\theta}$ and $\underline{\theta}$ are set in such a way that we can differentiate two dominance regions for θ (one for $\theta \leq \underline{\theta}$ and one for $\theta \geq \overline{\theta}$) and an intermediate region (for $\theta \in \left(\underline{\theta}, \overline{\theta}\right)$) which, in the presence of complete information, would exhibit multiple equilibria. Notice that in this intermediate region the optimality of taking action A heavily depends on the expectation that agents have about θ with respect to T. In order to make the game non-trivial, T is assumed to be strictly smaller than $\overline{\theta}$.

Once θ is realized, independent signals are privately drawn for each player according to a normal distribution with mean θ and standard deviation σ:

$$x_i \sim N(\theta, \sigma^2)$$

Given that players do not observe θ directly, once they observe their signal they base their decision to take action A or B on the expectations about θ and about the likely action of the other player. In particular, once they observe their signal players update their beliefs about θ and make inferences about the probability of θ being in either of these three regions. If they believe that θ might be in the intermediate region then players have to form an expectation of the likely action of the other player, since in this region players need to coordinate in action A in order for action A to yield a high payoff.

As first proven by Carlsson and van Damme (1993), in these type of games the information structure leads players to use a monotonic decision rule in which they take action B for low realizations of their signals, and they take action A for high realizations of their signals. This effectively means that agents use a threshold strategy such that they take action A if their signal is higher than a certain cutoff, $x^*(\sigma)$, and they take action B if their signal is lower than $x^*(\sigma)$. Formally, this decision rule can be written as:

$$a(x_i; \sigma) = \begin{cases} A \text{ if } x_i \geq x^*(\sigma) \\ B \text{ if } x_i < x^*(\sigma) \end{cases}$$

The threshold $x^*(\sigma)$ is defined as the value of the signal for which an agent is indifferent between taking action A or B.[7] This means that when an agent observes signal $x^*(\sigma)$, the expected payoff of taking action A is equal to the expected payoff of taking action B, which is zero in this case. Formally, if we assume that agents use threshold strategies in equilibrium, $x^*(\sigma)$ is the unique solution to the following equation:[8]

$$\begin{aligned} E\left[\theta \mid x_i, x_j \geq x^*, \theta \in (\underline{\theta}, \bar{\theta})\right] \times \Pr(x_j \geq x^* \mid x_i, \theta \in (\underline{\theta}, \bar{\theta})) \times \Pr\left(\theta \in (\underline{\theta}, \bar{\theta}) | x_i\right) \\ + E\left[\theta \mid x_i, \theta \in [\bar{\theta}, \infty]\right] \times \Pr(\theta \in [\bar{\theta}, \infty] | x_i) - T = 0 \end{aligned} \tag{1}$$

We can see in equation 1 how expected payoffs depend on the value of θ and on the action of the other player. Recall that action A yields a payoff of $\theta - T$ under two conditions. Either $\theta \geq \bar{\theta}$, or $\theta \in \left(\underline{\theta}, \bar{\theta}\right)$ and the other player also takes action A. The first condition is captured by the second term of equation 1 which simply corresponds to the conditional expectation of θ times the probability of θ being in this region. The second condition is captured by the first term of equation 1, which corresponds to the expected value of θ times the probability of coordinating with the other player (i.e. the probability that the other agent observes a signal $x_j \geq x^*(\sigma)$, which leads him to takes action A as well), times the probability of being in the intermediate region $(\underline{\theta}, \bar{\theta})$, everything conditional of the private signal x_i. Taking action A always has a cost of T, irrespective of the value of θ, so we subtract it in equation 1. Finally we equate the expected value of taking action A

[7] Note that the value of the threshold depends on the precision of the signal, which in the case of a normally distributed signal is equal to the inverse of its variance. In this case, the precision of the private signals is equal to σ^{-2}.

[8] A unique solution to equation (1) is ensured as long as the private signals are precise enough with respect to the prior, i.e. when $\frac{\sigma}{\sigma_\theta} < K$, where σ_θ is the standard deviation of the prior about θ and K is a constant that depends on the parameters of the model. This is a standard condition in the global games literature and it is met for the parameters used in the experiment (for a detailed discussion about the conditions for uniqueness see Theorem 1 in Szkup and Trevino, 2014).

to zero, which is the payoff of taking action B, to find the value of the threshold that equalizes the expected value of both actions. Note that, by definition, when an agent observes a signal that has exactly the same value as the threshold he does not have any strict preference over actions. This effectively means that for these signals agents are not sure about which action would yield a higher payoff in expectation.

In the RT analysis that follows we do not assume that the threshold used by subjects is the equilibrium threshold predicted by the theory. Since subjects do not necessarily use the equilibrium threshold they might have mistaken beliefs that make them indifferent between actions. Therefore, when we talk about high RTs being related to indifference between their binary choices, we do not necessarily refer to the theoretical equilibrium indifference portrayed in equation 1.

2.1 Parameters used in the experiment

The global games model presented above is governed by a set of parameters $\Theta = \left\{\mu_\theta, \sigma_\theta, (\underline{\theta}, \overline{\theta}), T, \sigma\right\}$. For the experiment, the parameters chosen are the following:

$$\Theta = \{50, 50, (0, 100), 18, 1\}$$

In particular:

- The fundamental θ is randomly drawn from a normal distribution with mean 50 and standard deviation of 50.
- The coordination region is for values of $\theta \in (\underline{\theta}, \bar{\theta}) = (0, 100)$.
- The cost of choosing action A is $T = 18$.
- The standard deviation of the private signals is $\sigma = 1$.

3 Experimental design

We present the results of an experiment to analyze the role that RT has on predicting choices in global games. The experiment was conducted at the Center for Experimental Social Science at New York University using the usual computerized recruiting procedures. The data generated by these experiments is a subset of the much larger data set generated by Szkup and Trevino (2016), whose emphasis was on the strategic play of the subjects and not on their RTs. The experiment was programed in z-Tree (Fishbacher, 2007).

All subjects were undergraduate students from New York University. Our experimental design is closely related to the work of Heinemann et al (2004), who test the predictions of the global games model of Morris and Shin (1998) and find clear support in the data for the use of threshold strategies. However, Heinemann et al (2004) do not analyze RTs.

In each session subjects play the game for 50 independent rounds. Our treatments vary according to the type of action choice (direct choice vs strategy method). In the treatment with direct choice of action subjects observe signals and then choose actions (as portrayed by the model in section 2), while in the strategy method treatment we elicit thresholds in every period before the subjects observe their signal in order to study the explicit evolution of thresholds over time.

Overall, we present the results of three sessions where we had a total of 58 participants. Table 1 summarizes our experimental design.

Treatment	# Sessions	# Subjects
Direct action choice (DA)	2	38
Strategy method (SM)	1	20

Table 1: Experimental design

Subjects were randomly matched in pairs at the beginning of each session and stayed with the same partner for all rounds. Each session lasted approximately 60 minutes and subjects earned on average $20.

The state θ is randomly drawn at the beginning of each round according to a normal distribution with mean 50 and standard deviation of 50. Once θ is drawn, one private signal is independently drawn for each subject from a normal distribution whose mean corresponds to the chosen value of θ and with a standard deviation of 1. In order to minimize the noise in RT observations, at the beginning of each round, subjects have to click on a button to observe the signal that was generated for them, and then they have to choose an action, for the treatments with direct action choice.[9] The time between when the button was clicked to observe a signal and the moment when the choice was made is our measure of RT. For the strategy method treatment, before observing a signal, subjects have to report the threshold above which they would be willing to take action A and below which they would be willing to take action B.

After each round, each subject observed his own private signal, his choice of action, the realization of θ, how many people in his pair chose A, whether the outcome was favorable to A, and his individual payoff for the round.

The computer randomly selected five of the rounds played and subjects were paid the average of the payoffs obtained in those rounds, using the exchange rate of 3 tokens per 1 US dollar.

4 Experimental results

We first present the analysis of the treatment with direct action choice to establish the results based on RT estimations and characterize subjects' behavior. We perform the data analysis by studying RT in the first 25 rounds, when subjects are getting acquainted with the game and deciding on a strategy, to predict observed thresholds in the last 25 rounds, once subjects have, presumably, converged to a stable behavior. We use our choice-based results of the last 25 rounds as the objective choice measures against which we compare our predictions based on RT.

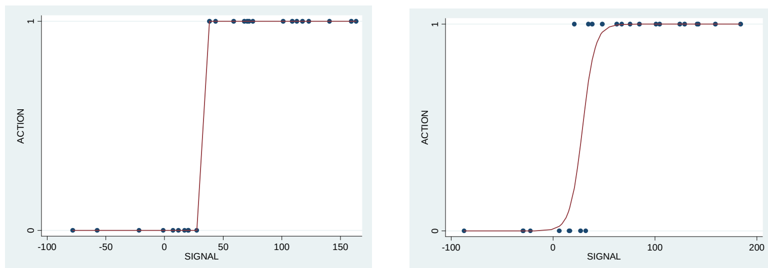
We then move on to the results of the strategy method treatment to evaluate the robustness of our earlier characterizations by performing some out of treatment estimations.

4.1 Choice based estimations

Just as in Heinemann et al (2004) we find that over 90% of our subjects use threshold strategies during the last 25 rounds of the experiment. We say that a subject's behavior is consistent with the use of threshold strategies if the subject uses either perfect or almost perfect thresholds. A perfect threshold is characterized by taking action B for low values of the signal and action A for high values of the signal, with exactly one switching point. This effectively means that the set of signals for which a subject takes action A and the set of signals for which he takes action B are disjoint. This type of behavior is illustrated in panel (a) of Figure 1, which has the signals a subject receives

[9] Having a subject click on a button gives more certainty in terms of when a subject actually first sees the signal, reducing the noise for cases when they might be day dreaming.

on the horizontal axis and a binary value (0 for action B, 1 for action A) on the vertical axis. For almost-perfect thresholds, we allow these two sets to overlap for at most three observations. This means that subjects take action B for low signal values and action A for high signal values, but these two sets can intersect for at most three observations. Such behavior is portrayed in panel (b) of Figure 1 where we fit a logistic function to the observed last-25 round data of a specific subject.



(a) Perfect threshold

(b) Almost perfect threshold

Figure 1: Examples of perfect and almost perfect thresholds

We observe the use of threshold strategies in 94.7% of our subjects in the DA treatment over the last 25 rounds of the experiment.[10] Once we have identified the subjects who use threshold strategies, we estimate the threshold for each subject by taking the average between the highest value of the signal for which a subject chooses action B and the lowest value of the signal for which he chooses action A in the last 25 rounds. This number approximates the value of the signal for which a subject switches from taking one action to taking the other action, which is how we define a threshold.[11] We find a mean estimated threshold of the group to be 26.53 with a standard deviation of 18.64.[12]

4.2 Response time estimations

We show in this section that during the first 25 rounds of the experiment, if we consider for each individual the signal for which he has the highest or second highest RT, then, on average, either of those signals is an unbiased predictor of the threshold that this subject employs in the last 25 rounds of the experiment. In other words, we use RTs in the first 25 rounds to predict the observed thresholds in the last 25 periods, once behavior has stabilized. We discard the first round because there is in general a lot of noise in the RT data (e.g. subjects are getting acquainted with the interface).

To make our case, we look at the difference between the signals associated with a subject's highest and second highest RT and that subject's eventual, last-25-round, threshold. If either of these signals are predictive of last 25-round thresholds, we would expect to see these differences distributed, perhaps normally, around zero.[13] The frequency distribution of these differences, for the highest, second highest, and third highest RTs, together with their CDFs, are portrayed in

[10] In particular, 78.9% of the subjects exhibit perfect thresholds and 15.8% exhibit almost perfect thresholds.

[11] For a complete characterization of choice-based measures for thresholds in a global game see Heinemann et al (2004) and Szkup and Trevino (2016).

[12] Notice that on average, subjects do not seem to follow the equilibrium threshold predicted by the theory, which corresponds to 35.31. However, the purpose of this study is not to establish optimality of thresholds with respect to the theory, but to predict observed thresholds with RT.

[13] Note that we do not expect to observe these differences to be exactly zero because individual thresholds are estimated numbers and the probability of getting a signal realization exactly equal to this number in the first 25 rounds is very small.

Figure 2 and summary statistics are presented in Table 2. As we can see, neither the mean nor the median of the distributions of differences between estimated thresholds and signals associated to the highest and second highest RT are statistically different from zero. For this reason, we can interpret the signals associated to the highest or second highest RTs as unbiased estimators of the observed thresholds in the sample. Moreover, these two distributions are not statistically different from each other using a Kolmogorov-Smirnov test (p value of 0.825). However, this is no longer the case for the signals associated to the third highest RT. Both the mean and median of the differences between estimated thresholds and the signals associated to the third highest RT are different from zero to the 1% level of significance, and the distribution of these differences is statistically different from the distribution of differences corresponding to the highest and second highest RT to the 1% level of significance, using a Kolmogorov-Smirnov test.

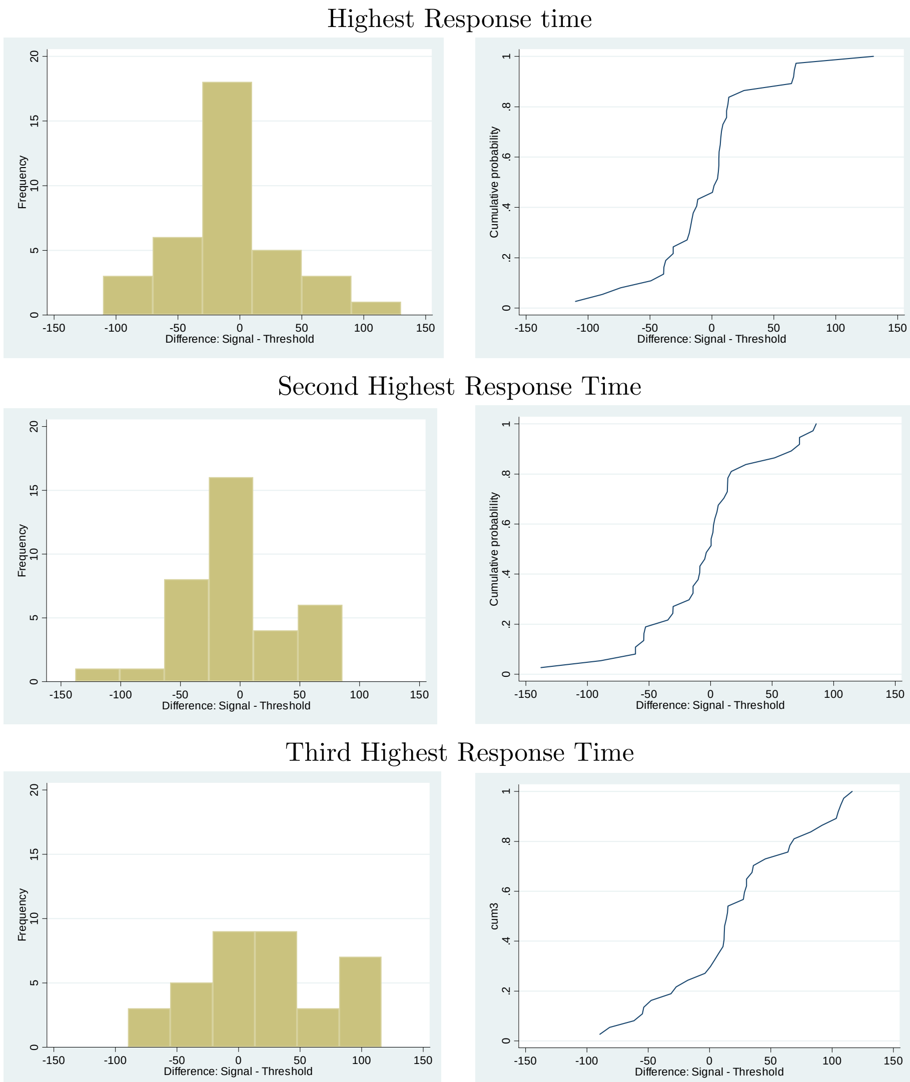


Figure 2: Histogram and CDF of the difference between individual thresholds and signals associated to the highest and second highest RT, DA treatment

To further investigate how robust our results are with respect to the predictions based on RT, we look also at the signals corresponding to the fourth highest RT, fifth highest RT, and so on,

	Mean (H0: $x = 0$)	Median (H0: $x = 0$)	Standard deviation
Highest RT	-4.01	3.17	43.83
p value	0.293	0.388	
2nd highest RT	-4.19	-1.54	47.78
p value	0.301	0.572	
3nd highest RT	20.92**	14.19**	55.67
p value	0.012	0.021	

Table 2: Summary statistics of the difference between individual thresholds and signals corresponding to highest and second highest RT, DA treatment

and the distribution of differences between these signals and the subjects' last 25 round thresholds. Figure 3 illustrates how the signals associated to the RTs after the first or second highest are no longer unbiased predictors of future choices, since the mean difference of the signals associated with these higher RTs and the last-25 rounds estimated thresholds are all significantly different from zero.[14] The graph in Figure 3 presents the mean of the distribution of differences between estimated thresholds and signals corresponding to the highest RT, second highest RT, third highest RT, fourth highest RT, up to the 24th highest RT, in the first 25 rounds of the experiment. In the horizontal axis we have the rank of the RT, starting from the highest at the origin to the 24th highest RT at the right end of the axis. On the vertical axis we have the mean difference between the signals corresponding to the nth highest RT and the observed thresholds, across subjects. Two dashed lines indicate confidence intervals (mean differences ±2 standard errors).

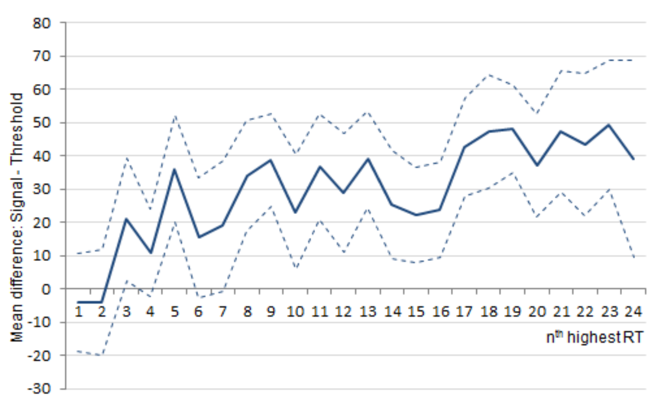


Figure 3: Mean differences between signals associated to RTs and thresholds, DA treatment

As we can see from Figure 3, only the highest and second highest RT are good predictors of future thresholds since only in those cases the mean difference between the signal corresponding to each of these RT and the eventual thresholds is not statistically different from zero. This suggests that the accuracy of RTs as predictors of observed thresholds drops dramatically when we move from the second longest to the third longest RT, and so on.

In terms of average length of RT, figure 4 shows the mean RT for the highest RT, second highest

[14] The mean of the distribution of differences is statistically different from zero to the 1% level of significance for all cases after the 2^{nd} highest RT, except for the following: for the 3^{rd}, 6^{th}, and 7^{th} highest RT the mean is different from zero to the 5% level of significance, and for the 4^{th} highest RT the mean is different from zero to the 10% level of significance.

RT, third highest RT, and so on, with lines for standard errors. Notice that the mean RT for the highest RT observations is 12.98 seconds and it is 8.35 seconds for the second highest RT, while the remaining RTs quickly decline and eventually converge to 2 seconds. Despite the fact that the mean RT for the third highest RT is close to that of the second highest RT (6.7 seconds vs 8.35 seconds), they are different to the 5% level of significance (p value of 0.027).

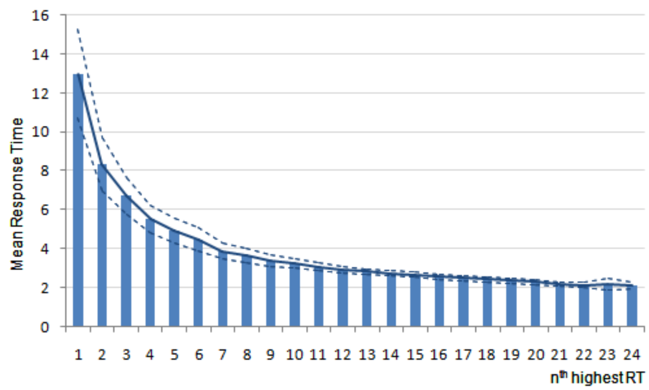


Figure 4: Mean RTs, DA treatment

It is relevant to point out that this are aggregate results. In other words, on average, across all subjects, either the first or second longest RT is an unbiased predictor of eventual thresholds. Obviously, as our figures indicate, there is a variance around this mean. This implies heterogeneity in the sample, which we study later on.

4.3 Comparison with other estimators

We now evaluate the predictive power of the signals related to either the highest or the second highest RT to the equilibrium predictions and to the predictions of the choice-based thresholds from the first 25 rounds.

Looking first at the theoretical equilibrium predictions, the second row from Table 3 shows the mean and median difference between the equilibrium prediction (a threshold of 35.31) and the observed last 25 rounds thresholds. As we can see, both the mean and the median difference are statistically different from zero to the 1% level of significance, indicating that the equilibrium predictions of the theory make rather poor predictions of actual eventual threshold behavior. This is in contrast to the signals associated to the highest and second highest RT, which, as Table 2 indicates, are unbiased predictors of future thresholds. Moreover, the mean and median difference between observed thresholds and equilibrium predictions are statistically different from the mean and median differences between observed thresholds and signals associated to the highest and second highest RT.[15] Therefore, we can conclude that, on average, the signals associated to either the highest or the second highest RT are better predictors of observed thresholds than the theoretical equilibrium prediction.

With respect to our second comparison, we ask how the predictions of eventual thresholds made on the basis of our RTs (a non-choice variable) compare to what we could get by if we measure thresholds in the first-25 rounds (choice based estimates). As we can see from Table 3, on average the thresholds estimated for subjects in the first 25 rounds are also good predictors of

[15] Medians are different to the 1% level of significance, using a rank sum test. Means are different to the 5% level of significance, using a t-test.

	Mean (H0: $x = 0$)	Median (H0: $x = 0$)	Standard deviation
Difference wrt equilibrium	8.79***	13.86***	18.89
p value	0.004	0.0002	
Difference wrt first-25-round thresholds	0.77	0.36	19.49
p value	0.813	0.937	

Table 3: Summary statistics of the difference between individual thresholds and equilibrium predictions, DA treatment

future behavior, just as the highest or second highest RT. This is interesting since it indicates that a non-choice variable (RT) can be as reliable a predictor of behavior as one based on choice data (first-25 round estimated thresholds). However, not all subjects that use threshold strategies in the last 25 rounds do so in the first 25 rounds. As we will see below, some of our subjects converge to a threshold by the end of the experiment by learning how to play the game, so their behavior in the first 25 rounds is not necessarily consistent with a threshold strategy.

4.4 Subject types

With these results in hand, we now investigate if our RT estimators can give us more information about the way in which subjects make their decisions. To aid us in this endeavor, we define the "Best Predicting Response Time" (BPRT) for each subject by looking at the signals associated with the highest and second highest RTs (the unbiased predictors of future thresholds), and selecting, for each individual, the signal that is closest to that subject's estimated threshold. Hence, for some subjects the BPRT will be associated to the signal with the highest RT, while for others it might be the signal with the second highest RT. This selection will facilitate the characterization of subjects into two different types.

Before presenting the two different types of subjects, we look in more detail at the BPRT observations. If the BPRT is meaningful to subjects, then we would expect their contemplation time to be different before and after they exhibit the BPRT. That is, we would expect subjects to spend less time thinking when they receive signals after their BPRT, since experiencing their BPRT should make them feel more confident about what actions they should attach to each future signal, and hence they should spend less time thinking. Table 4 contains the mean and median RT corresponding to the BPRT observations, observations before the BPRT, and observations after the BPRT. As is shown in this table, the mean and median RTs are lower after subjects have experienced their BPRT and this difference is significant at the 1% level. Note that when subjects receive the signal associated to their BPRT, they spend, on average, 10.10 seconds thinking about it, while for signals received before their BPRT they spend 3.97 seconds, and after the BPRT they spend only 2.88 seconds, on average. Therefore, we interpret the high contemplation time of the BPRT as reflecting the fact that, given the signal observed, it is not obvious for subjects what action to take, thus they need more time to deliberate.

	Mean	Median	St. dev.
RT exactly at BPRT	10.10	8.17	5.96
RT from $t \in \left[2, t_i^{BPRT}\right)$	3.97	2.95	3.08
RT from $t > t_i^{BPRT}$	2.88	2.49	1.64

Table 4: Summary statistics of distributions of RT before, after, and at BPRT, DA treatment

The results presented so far give us an indication that subjects behave differently pre and post BPRT, which implies that their extended thinking at the BPRT imparts some knowledge. Our presumption is that at this point they gain some certainty about the value of their threshold and thus know what their behavior rule should be, so that after this discovery their RT is less sensitive to the signal they observe. This is consistent with the interpretation that a threshold strategy corresponds to the value of the signal for which a subject is indifferent between taking either action, that is, the signal for which the subject is not sure about which action to take.

We now make use of the BPRT to characterize the reasoning that leads subjects to think longer at that point by distinguishing between two different types of people, which we call Intuitionists and Learners. As described in the introduction, Intuitionists are subjects who act consistently with having an intuition about their threshold from the very beginning of the experiment. These subjects act as if they know what their threshold should be, but can't fully articulate or recall it. However, once they observe a signal close enough to their eventual threshold, they stop searching. On the other hand, Learners are subjects who might understand what threshold behavior is, but who must learn from experience what their personal threshold should be.

This distinction between Intuitionists and Learners should be observable in the RT data.[16] While Intuitionists can be expected to ignore signals far from their implicit threshold and think hard when they observe a signal close to it for the first time, Learners may receive a signal close to their eventual threshold and ignore it, since they are learning about what their threshold should be and may not recognize a good signal when it first arrives.

As a consequence of this distinction, we would expect that the first time an Intuitionist observes a signal close to her eventual threshold, that signal would become her BPRT, while a Learner may experience several such signals in early periods without those signals becoming a BPRT. We use this distinction and classify subjects as Intuitionists if they do not observe a signal closer to their eventual threshold before they observe the signal associated to their BPRT, while we classify them as Learners if they do.

To give a simple example, say that a subject settles on a threshold of 25 in period 26-50 and in the beginning of the experiment receives signals of 10, 55, 3, 22 (in that order). Say 22 becomes her BPRT, in the sense that she spends more time thinking about that signal than any other signal received in periods 1-25. Since there was no other signal closer to 25 received before that BPRT was determined, we will classify this subject as an Intuitionist. Now, say we have another subject who also settles down to a threshold in periods 26-50 of 25, but receives the following signals before receiving her BPRT: 10, 55, 3, 22, 24, 67, 29. Note that if 29 becomes this subject's BPRT then she is spending a lot of time thinking about it, despite the fact that she had earlier received signals closer to her eventual threshold. Since this subject did not stop when she received signals closer to her threshold than what eventually became her BPRT, she must have been learning when those signals arrived, so we would classify this subject as a Learner.

This distinction between Intuitionists and Learners should manifest itself in the individual behavior of our subjects and the data they generate. More precisely, we expect certain differences in the behavior of subjects we classify as Learners and Intuitionists. First, because Learners find the value of their threshold with experience while Intuitionists implicitly know it, we would expect Intuitionists to experience their BPRT in earlier periods than Learners (Learners need more time to learn, given identical signal distributions). Second, by a similar argument (i.e. that Learners have to learn what their threshold is while, implicitly, Intuitionists know it from the outset), we

[16] Our use of term Intuitionist differs from Rubinstein (2007). For Rubinstein intuitionists tend to have lower RTs to a given problem, while in our paper there is no particular difference between the duration of the first or second longest RTs for Intuitionists and Learners. What we find is that Intuitionists discover their threshold in earlier rounds than Learners.

would expect that Intuitionists would behave in a manner consistent with their ultimate last 25 round thresholds from the very beginning of the experiment. In other words, Intuitionists have a better understanding about what their threshold is while Learners need to learn it, so if we estimate two different thresholds for each Intuitionist and Learner -one for the first and one for the last 25 periods- and then calculate the difference between these estimated thresholds, we would expect to see a much smaller difference between these estimated thresholds for Intuitionists than for Learners. This would imply that the thresholds of Intuitionists are more stable over time than the thresholds of Learners.

We now explore each of these differences between Intuitionists and Learners in detail.

Figure 5 illustrates the first point, which plots, for each group, the distribution of periods corresponding to the BPRT, and Table 5, which presents the mean and median of these distributions. Just as we expected, on average Intuitionists realize their BPRT in earlier periods than Learners. In particular, Table 5 indicates that while the average Intuitionist experienced his BPRT around period 7, it took Learners on average until period 15 to do so. The medians exhibit an even stronger difference with half of the Intuitionist experiencing their BPRT by period 3 or 4, while half of the Learners took until period 16 to do so. Both the means and the medians are statistically different at the 1% level.[17]

Finally, as we see in Figure 5 the two distributions of BPRTs appear considerably different, with the Intuitionists distribution exhibiting far more of a right skew and a mass on lower periods. In particular, these two distributions are statistically different to the 1% level using a Kolmogorov-Smirnov test.

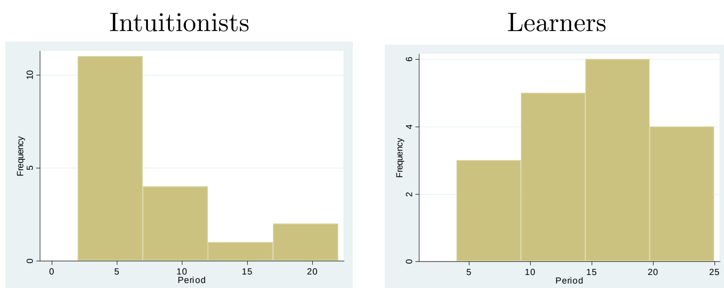


Figure 5: Distribution of BPRT periods, by group, DA treatment

	Mean	Median	St. dev.
Learners	14.89	16	5.32
Intuitionists	7.44	3.5	6.5

Table 5: Summary statistics of BPRT periods, by group

Because Intuitionists are expected to behave according to their eventual last-25 round thresholds from the beginning of the experiment, while Learners are not, we might expect the thresholds used by Intuitionists to be relatively stable across the first and last 25 rounds, while the thresholds used by Learners may change due to learning. Hence, if we were to compare individual thresholds

[17] Such a difference might lead one to think that perhaps a better way to classify subjects would be by calling them either fast or slow learners and choosing some arbitrary number of periods before a BPRT is determined to separate them. While this would have the benefit of being an exogenous classification scheme (ours is not exactly exogenous, it would offer no explanation as to why some subjects are fast and some slow and would be unable to offer any insights into the stability of behavior in our SM treatment to be discussed later on.

estimated in the first 25 rounds to the thresholds estimated in the last 25 rounds then, as mentioned above, the thresholds of Intuitionists should be more stable across the first and last 25 rounds than the thresholds of Learners. In Figure 6 we plot, for each subject, the differences (in absolute value) between their own estimated threshold in the last 25 rounds and the threshold we estimate for them in the first 25 rounds. Each bar corresponds to one subject, black bars correspond to Intuitionists and grey bars to Learners. Within each group the bars are displayed in ascending order of the absolute value difference. Table 6 reports, for each group, the mean difference of first and last 25-round thresholds (in absolute value) and the standard deviation of the distribution of these differences. We can observe smaller variations between thresholds, on average, for Intuitionists.

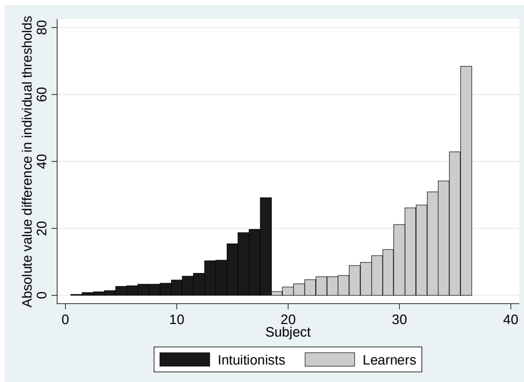


Figure 6: Differences of individual thresholds (in absolute value) from first 25 and last 25 rounds, by group and in ascending order, DA treatment

	Mean	Median	St. dev.
Learners	17.95	10.83	17.71
Intuitionists	7.76	4.07	8.07

Table 6: Summary statistics of differences in individual thresholds from first 25 and last 25 rounds, by group, DA treatment

As is clear from Figure 6, there is far less variability in the individual estimated thresholds of Intuitionists than there is among Learners. For example, the mean difference between first-25 and last-25 round thresholds (in absolute value) for Learners is 17.95, while for Intuitionists it is only 7.76, and these means are different to the 5% level of significance. A Wilcoxon test rejects the hypothesis that the sample of threshold differences in absolute value came from the same population at the 5% level. Moreover, the variances of these two distributions are different to the 1% level. This clearly implies that Intuitionists seem to have a clearer sense of what their threshold is in the earlier rounds of the experiment when compared to Learners, thus exhibiting more stable thresholds over time.

It is important to note, however, that in the last 25 rounds the subject behavior across types is indistinguishable from one another, since they all use thresholds and the mean estimated thresholds for each group are not statistically different from each other. Table 9 in the appendix presents summary statistics about their observed threshold behavior in the last 25 rounds.. This illustrates how RT analysis might give a broader insight about decision making than just choice data. By studying RTs in the first rounds of the experiment we are able to distinguish how the different types of subjects come to realize their thresholds.

4.5 Out-of-treatment predictions

One exercise that has proven to be informative (see Caplin and Dean, 2015) is to axiomatize the behavior of economic agents and then characterize what the data from an experiment must look like if subjects behave in a manner consistent with those axioms. In other words, in a revealed preference type of exercise, one looks to see what the implications are for choice data of behavior that satisfied a set of assumptions or axioms. In this section of the paper we would like to ask a similar question with respect to our characterization of Intuitionists and Learners. While we have proposed no axioms, if our characterization of types is successful we should be able to distinguish between subjects based on their exhibited behavior in the first rounds of the experiment.

The question is simple: If we performed a treatment where, instead of giving subjects a signal and then asking them to choose an action, we asked them before each period to state a threshold or cutoff level for realized signals above which A would be chosen, but below which B would be chosen, would we be able, from observing their reported thresholds, to classify subjects as Learners and Intuitionists? In other words, we are asking if we can observe Intuitionist and Learner behavior in an out-of-treatment exercise. To answer this question we make use of the data from our SM treatment, where subjects play the same game as before but where, instead of observing signals and choosing actions directly, we use the strategy method to ask subjects to report their threshold.

If our characterization of types is correct, then we should observe a group of subjects who report very stable thresholds from the initial rounds of the experiment, which would correspond to Intuitionists and another group, the Learners, whose period to period thresholds should exhibit far more variability in early rounds due to experimentation, and then stabilize. Our results indicate that by looking at the evolution of reported thresholds throughout the 50 rounds of the experiment we can categorize 80% of the subjects in this treatment in this fashion. To perform this characterization we look at subjects who show some stability in reported thresholds in the last 25 rounds, to ensure convergence of behavior, and measure the standard deviation of their individual reported thresholds in the first 25 rounds. The data gives us a straight forward distinction between the subjects that we can potentially categorize as Learners and Intuitionists, in the sense that there is a group of subjects that exhibit low individual standard deviations of reported thresholds in the first 25 rounds (0 to 4.26) and a group of subjects with very large standard deviations (9.95 to 25.54). To give a better idea for how Intuitionists and Learners differ, consider Figure 7 which offers an example of the evolution of reported thresholds for one subject categorized as Intuitionist (left panel) and one as Learner (right panel). Figures 8 and 9 in the appendix plot these graphs for all subjects categorized in either of these groups.

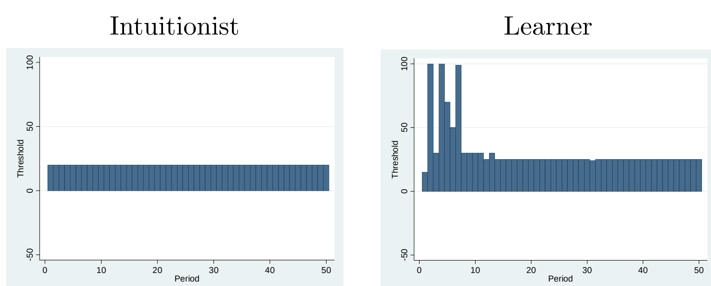


Figure 7: Examples of evolution of thresholds in SM treatment, by group

As we can see, the panel on the left offers a perfect picture of what our archetypal Intuitionist should look like in the SM Treatment. Previously we characterized Intuitionists as subjects who have a good idea of what their threshold should be but cannot explicitly verbalize it. In the

DA treatment, subjects observe signals and implicitly set a threshold, whereas in this treatment (SM) they are forced to report it. This implies a different psychological process when establishing an action rule, which forces Intuitionists to explicitly verbalize their threshold. In line with our original description, Intuitionists act consistently with their threshold from the beginning of the experiment. Learners, on the other hand, are defined as subjects who are not quite sure what the right threshold should be and thus experiment in the initial rounds (see right panel in Figure 7). For the SM treatment this would imply that Learners set many different thresholds in the initial periods, and then converge to a threshold. To support this claim, in Table 7 we present summary statistics for the individual period-to-period changes in reported thresholds in the first 25 rounds, by groups, and we find that the mean period-to-period change in reported thresholds for Intuitionists is 0.80, while for Learners it is 12.30, with standard deviations of 2.51 and 16.36, respectively. Means, medians, and standard deviations are significantly different at the 1% level. As a result, it seems clear that for one group of subjects (whom we label as Intuitionists) there is very little variability in the thresholds they set in early rounds while in another (whom we label Learners) there is quite a bit of variation. This is in line with our categorization of subjects into these two groups.

	Mean	Median	St. dev.	N
Learners	12.30	6	16.36	7
Intuitionists	0.80	0	2.51	9

Table 7: Summary statistics of differences in individual reported thresholds in the first 25 rounds in the SM treatment, by group

Consistent with our previous results in the DA treatment, if we only looked at the last 25 rounds, both groups of subjects exhibit very stable thresholds, making them indistinguishable.

5 Discussion: Related Models

In this section we discuss three existing models that could potentially make predictions for our data by relating high RTs to choices between two alternatives that have similar valuations to the decision maker. We investigate the predictions of these three models for our experiment and find some, but limited, support for them for the aggregate data (pooled across subjects), and mixed evidence for individual behavior, which is what we aim at understanding. More precisely, we will demonstrate that each of the models we describe below makes an identical qualitative prediction, which is that RTs should be decreasing in the distance between the signal that a subject receives and his threshold. Put differently, individual RTs should be a concave function of the signals received by a subject, with a maximum for signals that coincide with the observed threshold. It is this prediction at the individual level that fails in our data.

The first model is the Drift Diffusion Model (DDM; Ratcliff, 1978, Ratcliff and McKoon, 2008), which is a widely used model in psychology and neuroscience that studies the way in which the brain compares values to make binary choices. One of the key outputs of this model is the RT of subjects in these tasks. This model assumes that decisions are made by a noisy process that accumulates information over time from a starting point toward one of the two responses (or boundaries), and a response is chosen once one of these boundaries is reached [20]. The rate of accumulation of the information is assumed to be determined by the quality of information extracted by a stimulus. Ratcliff and McKoon (2008), for example, use a motion discrimination task where the stimulus is composed by a set of dots in a circle and, in each round, a proportion of the dots moves coherently either to the left or to the right, and the rest of the dots move in a random direction. The task for subjects is to decide in which direction the coherent dots move. When varying the proportion of dots that move coherently, they find that higher RTs are associated to higher levels of difficulty (i.e. low coherence) and to an almost equal probability of choosing the right and the wrong direction. On the other hand, when a high proportion of the dots move coherently, subjects make the right choice more often and they exhibit lower RTs. What this effectively means is that higher RTs arise as decisions become harder for subjects because they cannot clearly assess what is the right choice, given the information presented to them. So for Ratcliff and McKoon (2008) a stimulus that is more coherent is one that gives subjects a better idea of what choice to make.

Mapping the DDM to our experiment is not as straight forward a task as one might think, since there are some differences between our experiment and the typical DDM experiment. One clear difference is that the DDM studies individual decision making, while our experiment involves strategic interaction. Another important difference is that in a typical DDM experiment subjects are faced with an environment where each trial in the experiment is independent from the last, so there is no carry over between trials. This is true in the original Ratcliff (1978) experiments as well as the more recent papers emanating from the Rangel lab (e.g. Milosavljevic et al, 2010, Krajbich and Rangel, 2011, Clithero and Rangel, 2013), where choices are made in a value-choice context. In our experiment, quite the opposite is true, since we present subjects with a learning task (they need to learn the best threshold to use), which involves arriving at the right set of expectations about the true state, but also about their opponent and his strategy. Information from previous trials is essential in this task and hence the trials are not independent from one another. A valid application of the DDM model to our context would therefore need to be a dynamic model where, based on previous experience, a subject updates the starting value of the DDM process. Such a model is beyond the scope of this paper. Finally, another important difference between our study and DDM studies is that we use RT to study individual learning processes, i.e. we study how each subject learns to set a threshold as he moves across rounds receiving different signals. In DDM experiments RT observations are typically aggregated across subjects, so the results reflect the aggregate behavior of the sample used in these experiments and not the individual process that leads each subject to behave in a certain way.

However, the DDM can, in a limited way, be used to think about the task facing subjects that we describe as Intuitionists. Consistent with our view of Intuitionists, the DDM can predict RTs in situations where, for example, subjects have to assess whether a certain number is higher than a fixed reference number (the Intuitionists' implicit threshold). According to the model for memory retrieval (Ratcliff, 1978), subjects might have a hard time remembering a reference number, and if they receive a stimulus in the form of another number and have to decide whether this stimulus is higher than the reference number, the DDM predicts higher RTs for numbers that are closer to the reference number, since they require subjects to make a higher effort when assessing its value with respect to the reference (i.e. for very high or very low numbers it is "easier" to decide that they are higher or lower than the reference number). In our context, we think of Intuitionists as subjects who hold a threshold in their head which they try to retrieve once they are presented with a signal in a given round. Using the DDM language, a more coherent signal could be an extreme value, either very high or very low, and very far from the subject's threshold, which should imply an easy choice for subjects and hence a low RT. Likewise, a less coherent signal would be one for which subjects cannot easily assess which action to take (in our case, because it is close to their eventual threshold), and this would be associated to a higher RT.

Bearing this in mind, the DDM would predict that subjects in our experiment should exhibit longer RTs as they receive signals closer to their personal thresholds and that RTs should decrease as signals get further away from their personal thresholds. In this sense, we should expect the relationship between signals and RTs to be concave with a maximum at the observed threshold for each subject.

A similar prediction arises from the model of Gabaix and Laibson (2005) and Gabaix et al (2006), that is tested in the experiment of Chabris et al (2009). These papers propose an optimization theory called the Directed Cognition Model (DCM), which is based on dynamic programming and assumes that agents have limited cognitive resources. When time is a scarce resource, the DCM predicts that agents will allocate more decision time to choices between options of similar expected utility than to choices between options of dissimilar utilities. Just as the DDM, the DCM would predict, in the context of our paper, an inverse relationship between RT and the distance between signals and thresholds.

It is important to point out, however, that the DDM and DCM are designed to analyze individual decision problems, and not games.

The third model that we present here is an interpretation, in terms of RT, of the canonical global games model, as presented in Section 2. From Equation 1 note that, by definition, when an agent observes a signal that has exactly the same value as the threshold, he does not have any strict preference over actions. This effectively means that for these signals agents are not sure about which action would yield a higher expected payoff. Interpreting this condition in terms of RT, a subject should exhibit a higher RT when confronted with signals that are closer to the subject's threshold than when observing signals that are far from it. This model, as the other two theories, would predict a concave RT function for each subject, with a maximum at the threshold chosen by them.

In summary, each of the models described above predicts that our RT data should be consistent with two stylized facts. First, we should find a negative and significant relationship between RT and the distance between signals and future individual thresholds (stylized fact 1). We explore this prediction by performing a random effects OLS regression for the data, pooled across subjects, that has RT as the dependent variable and the difference (in absolute value) between the signal associated to each RT and the individual threshold that each subject converges to in the last 25 rounds as the independent variable. Second, since the RT function is predicted to be concave, we should be able to fit, for each subject separately, a concave function where on the horizontal axis we would have the value of the signal observed (positive or negative), and on the vertical axis the RT associated to that signal. In addition, we would expect that the maximum of this concave function should correspond to the threshold that each subject converges to in the last 25 rounds (stylized fact 2).

Bearing our caveats in mind about the applicability of the DCM and DDM models to our data, we test the predictions of stylized facts 1 and 2 above. In the DDM and the DCM models these stylized facts should describe behavior in all rounds of the experiment, while in our analysis, once the BPRT is reached, a subject should stop contemplating each signal and simply choose A or B, depending upon whether it is above or below the threshold they have discovered. This is expected to be true whether the subject is classified as a Learner or an Intuitionist. In either case, the choice is expected to be made quickly and independently of the signal since, after the BPRT, the threshold is known and no more thinking is needed. Hence, if we find that there is a negative relationship between RT and the distance between signals and thresholds only holds for periods up to the BPRT and not beyond, then this would only show partial evidence for the DDM and DCM and be consistent with our RT observations.

In order to investigate whether stylized fact 1 is true or not, we run a series of OLS random effects regressions, reported in Table 8. In specification 1 we have RT as the dependent variable and the difference (in absolute value) between the signal and the threshold as the independent variable. We observe a negative and significant relationship between these two variables, just as hypothesized by the DDM and DCM. In specification 2 we add a variable for the round in which each decision takes place because we know that, on average, RTs decrease as we move across rounds, and find that the previously established relationship still holds, which again supports the DDM and DCM models. Specification 3 is similar to specification 2, with the addition of a coefficient for the Period squared, since in later rounds there is a flattening of RTs.

The results in specifications 1-3 support stylized fact 1 (significance for the variable | signal - threshold |), and thus for the predictions of the DDM and DCM. Note that these regressions are run on data generated by all of our subjects, i.e., both Learners and Intuitionists. The fact that we get significant results, therefore, is notable since we do not necessarily posit that the relationship will hold for Learners. To separate our conjecture from the DDM and the DCM we run specifications 4-6, where we include two more independent variables. One is a dummy that takes the value of 1 for periods up to the BPRT (D(BPRT) in the table), and zero for the remaining periods, and the other variable is an interacted term that multiplies this dummy to the absolute value difference between the observed signal and the individual threshold. When we introduce this control for the periods before and after the BPRT, we find that the influence of the signal (or its distance from the threshold) is significant only for the periods up to the one corresponding to the BPRT, but not after, which supports our conjectured behavior. In other words, subjects seem to exhibit periods of active consideration only up to their BPRT period, where they behave as if they discovered their optimal threshold and not beyond. Therefore, we find only partial evidence for the DDM and DCM predictions, and we find that our RT observations are meaningful in terms of these predictions.

	1	2	3	4	5	6
| signal - threshold |	-0.011***	-0.012***	-0.012***	-0.004	-0.005	-0.005
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.006)
| signal - threshold |×D(BPRT)				-0.015***	-0.016***	-0.017***
				(0.006)	(0.006)	(0.005)
D(BPRT)				2.399***	1.801***	1.776***
				(0.349)	(0.387)	(0.386)
Period		-0.103***	-0.301***		-0.064***	-0.26***
		(0.014)	(0.063)		(0.018)	(0.065)
Period^2			0.007***			0.007***
			(0.002)			(0.002)
Constant	4.38***	5.818***	6.826***	3.364***	4.517***	5.553***
	(0.21)	(0.29)	(0.428)	(0.259)	(0.42)	(0.53)

Clustered (by subject) standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8: RT as a function of the distance between signals observed and individual thresholds

Stylized fact 2 posits that when we disaggregate the data the graph of RTs for each individual will be concave in their signal, with a maximum at their last-25-round observed threshold. To explore this prediction we present Figure 10 in the appendix, where we plot the graphs for each subject (be they a Learner of Intuitionist) fitting a quadratic function between signals and RTs. Due to the regression results presented in Table 8, since the hypothesized relationship between RT and the distance between signals and thresholds is significant only until the period corresponding to the BPRT, we take, for each subject, the observations up to the BPRT period in the plots shown in Figure 10. Each plot has on the horizontal axis the value of the signal (positive or negative) and on the vertical axis the RT associated to each signal. Dots correspond to individual observations and the vertical line illustrates the value of the threshold estimated for each subject in the last 25 rounds. From this figure, note that when we disaggregate the data and look at individual behavior, it is not that clear whether or not we see an overall concave relationship between RT and distance between signals and thresholds, across subjects. Even though we might see this type of relationship for a small proportion of subjects, we cannot generalize this observation. This again fails to support the DDM and DCM predictions.

To take a further step in investigating this prediction, in Figure 11 in the appendix we show these plots only for Intuitionist subjects, since, as explained above, their behavior should be more consistent with the predictions of the DDM. Looking at these plots, notice that, even if there is a higher proportion of subjects that exhibit what looks like a concave relationship between signals and RTs, we still cannot fully confirm the predictions of these alternative theories in our data.

5.1 Strategic considerations

Studying RT in a game might bring a layer of complexity that is not present in individual decision making tasks. In our setup, for example, one might believe that subjects who fail to coordinate with their partners across the different rounds of the experiment are more likely to exhibit longer RTs on average. In other words, since subjects are not sure about the action that their partner will take, in every round it takes them a longer time to make a decision because they are constantly trying to adjust to their changing beliefs about their opponent's strategy.

To explore this possiblity we look at the data at the pair level. We create a measure of convergence of behavior within a pair by taking the absolute value difference between the thresholds in the last 25 rounds of each pair member. We study whether a higher distance between the thresholds in a pair (less convergence) leads to higher RTs. Table 10 in the appendix reports the results of a similar regression to specification 2 above, but where we account for the distance between thresholds in a pair. We find no such effect.

We do a similar analysis looking at the types that we have described above, Intuitionists and Learners, since the behavior of the former is more stable and does not seem to be adjusted from round to round, while the behavior of the latter is the opposite. In that sense, it is important to understand if these types are endogenous in the sense that the matching protocol affects whether a subject becomes an Intuitionist or a Learner. In other words, is it the case that Intuitionists exhibit stable behavior from the get go because they are more likely to be matched with an Intuitionist and learn their partner's strategy early on, while Learners might take longer to set a threshold because they are matched with other Learners like themselves. We do not find any evidence that is consistent with this type of reasoning. In particular, over 76% of pairs are composed by one subject who is classified as an Intuitionist and one who is classified as a Learner, and the mean and median differences in threshold behavior within pairs are not statistically different from those of the pairs that are constituted by subjects who are both Intuitionists or Learners. Likewise, the mean and median differences in threshold behavior within pairs are not statistically different for pairs of Learners and pairs of Intuitionists.[18]

6 Conclusion

In this paper we have attempted to gain insights into the thought process of subjects engaged in global games using the response times of their decisions. Quite remarkably, we have found that by looking at the highest or second highest response time exhibited by subjects in the early rounds of

[18] This lack of statistical significance is expected since there are very few data points to have sufficient power.

the experiment we can predict, on average, the eventual threshold they use in future rounds. This result is rather striking since response times are used not only as a way to gain qualitative insights into how different choices are represented in the decision making process, but rather as a tool to predict future choices. We know of few papers that attempt to do this.

In addition, we have presented evidence that these high response times represent different thought processes for different types of subjects. Based on the best predictor among the two highest response times, we classify subjects as Intuitionists and Learners and differentiate their behavior in the initial rounds of the experiment. This classification allows us to understand the different reasoning processes that lead different subjects to choose a similar threshold. That is, if one were to only look at choice data these two groups would be indistinguishable in terms of the thresholds they eventually set. In this sense, studying response times gives us an additional insight into the thought process that leads to setting a strategy in a global game.

We have also presented evidence in support of our distinction between Intuitionists and Learners in an out-of-treatment exercise. We observe behavior consistent with these two different groups in this new treatment, which illustrates that our categorization of subjects into types might be meaningful.

Finally, we look at the predictions of alternative models of cognition in the context of our paper and find mixed evidence about their predictions when analyzing behavior at the individual level.

In short, our paper provides an interesting insight into the usefulness of response times in the explanation of choice in global games.

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7 Appendix

	Learners	Intuitionists
N	18	18
Mean threshold	27.14	25.91
Median threshold	22.39	15.08
Standard dev.	22.51	21.02

Table 9: Summary statistics of estimated thresholds in the last 25 rounds, by groups, DH treatment

Intuitionists

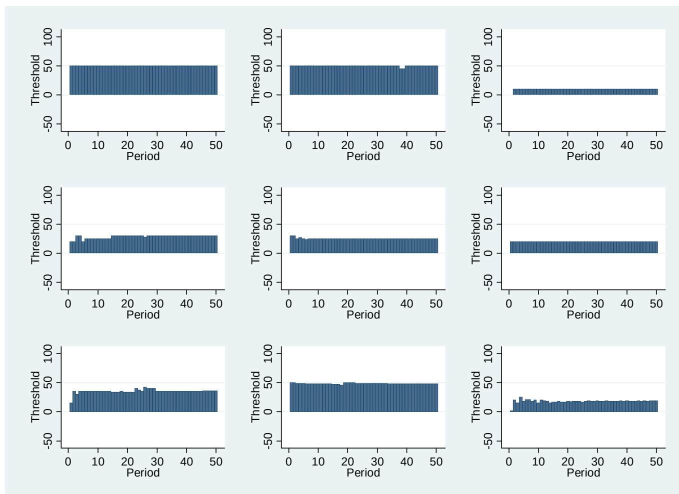

Figure 8: Evolution of reported thresholds for intuitionists, SM treatment

Learners

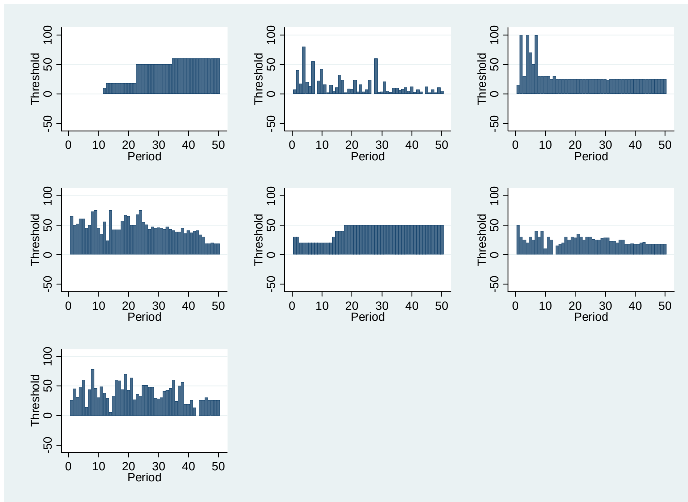

Figure 9: Evolution of reported thresholds for learners, SM treatment

	7	8
$\mid$ signal - threshold $\mid$		-0.013***
		(0.003)
$\mid$ threshold$_i$ - threshold$_j$ $\mid$	0.019	0.016
	(0.019)	(0.019)
Period	-0.104***	-0.107***
	(0.015)	(0.014)
Constant	5.09***	5.77***
	(0.03)	(0.333)

Clustered (by subject) standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 10: RT as a function of the distance between signals observed and individual thresholds, difference between thresholds in each pair, and period

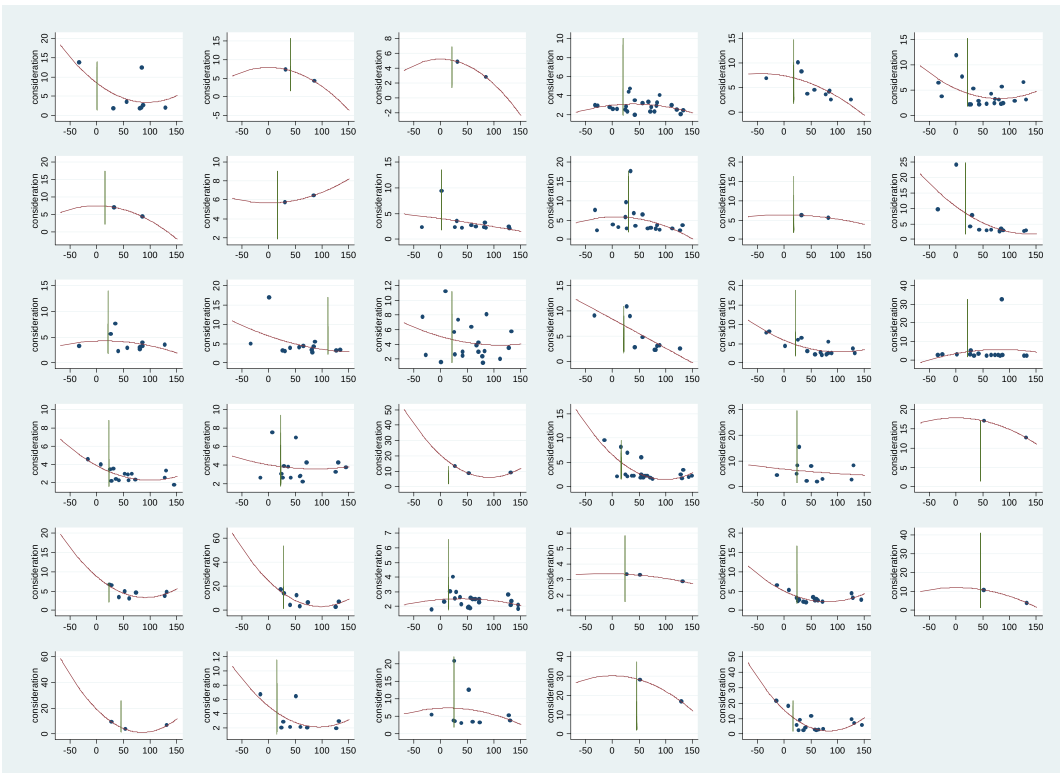

Figure 10: Quadratic fit of RT as a function of the signal value, by subject, DA treatment

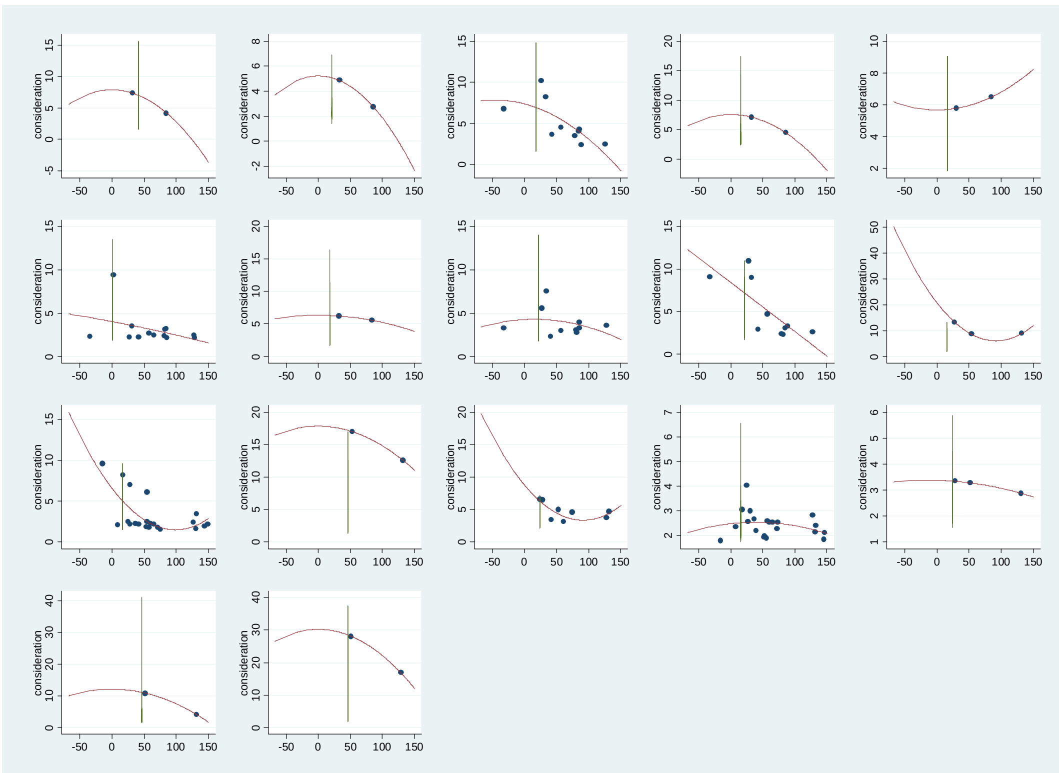

Figure 11: Quadratic fit of RT as a function of the signal value for Intuitionists, by subject, DA treatment