

Introspection in one-shot traveler's dilemma games

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Abstract: We report results of one-shot traveler's dilemma game experiments to test the predictions of a model of introspection. The model describes a noisy out-of-equilibrium process by which players reach a decision of what to do in one-shot strategic interactions. To test the robustness of the model and to compare it to other models of introspection without noise, we introduce non-binding advice. Advice has the effect of coordinating all players' beliefs onto a common strategy. Experimentally, advice is implemented by asking subjects who participated in a repeated traveler's dilemma game to recommend an action to subjects playing one-shot games with identical parameters. In contrast to observations, models based on best-response dynamics would predict lower claims than the advised. We show that our model's predictions with and without advice are consistent with the data.

Keywords: game theory, introspection, experiments, simulations, noisy behavior.

JEL Codes: C63, C72, C92

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1. Introduction

Most would agree that equilibrium in games is a result of some learning or evolutionary process by which subjects rid of biases in beliefs and update their choices while repeatedly playing the game. However, what if such a process is absent altogether?

In this paper we present a model designed to describe the thought process that precedes an action in one-shot games, where it is common knowledge that there is no chance of learning due to repetition or observation of others' past choices.¹ Indeed, we believe that the determination of what to do in an environment without repetition requires agents to "solve" the game through some introspective process. Thus, instead of focusing on equilibrium models to find a prediction for games played only once, we model the thought process that precedes an action. Of course, equilibrium should not be ignored, but should be thought of as a state that is achieved after learning due to repetition and/or observation

Our model is inspired by Bram's (1994) *Theory of Moves*, where he proposes modeling strategic decision making in the form of reasoning chains and is based on Capra's (1999) noisy model of introspection, which adds noise to the reasoning process. In our model, the reasoning process consists of calculating what one should do given some possible actions by the others, and then calculating the others' response, iteratively until a stopping rule is satisfied. We assume two kinds of cognitive limitations. 1) Responses follow the logit rule; that is, players do not iterate *best* responses² and 2) the beliefs that determine choice probabilities are degenerate distributions that put all of the probability mass into a single point. This assumption implies that, as players calculate responses, they

¹ See Weber, 2003 for evidence of learning in repeated interactions without feedback.

² The logit rule has the desirable property that response probabilities are a function of the player's payoffs and contains a parameter that measures the deviation from a best response. Better responses are more likely to be considered than worse responses, but best responses are not considered with certainty. See McKelvey and Palfrey (1995, 1998) for equilibrium models with probabilistic responses. Note that the model introduced by McKelvey and Palfrey is an equilibrium model, where belief probabilities must be consistent with decision probabilities in equilibrium. Our model is an out-of-equilibrium model with noise.

do not keep track of response probabilities p , for $0 < p < 1$. Thus, our model introduces bounded rationality and errors in decision making and hence differs from other models similar in spirit (i.e., introspective) such as Bernheim's (1984) and Pearce's (1984) *rationalizability*, Harsanyi and Selten's (1988) *tracing procedure*, Stahl's (1993), Stahl and Wilson's (1994) *n-level rationality*, and Camerer, Ho, and Chong's (2003) *cognitive hierarchies*.³

In addition, we present data from a series of one-shot traveler's dilemma games introduced by Basu (1984) that can be accurately explained by our model of introspection. We use the traveler's dilemma game to test the predictive power of the model because in this game "reasoning chains" are likely to occur.⁴ Comparisons between the data and simulations show that our introspective model is a good predictor of observed behavior. In addition, to test the robustness of the model against other models of introspection without noise, we look at the effect of non-binding common advice on decisions. Common advice works as a way to coordinate players' beliefs onto a single point. Experimentally, we introduce non-binding advice by making public a "best choice" advice that players of a repeated traveler's dilemma game give to subjects playing single interaction games with the exact same parameters. We compare the predictions with predictions made by other models of introspection.⁵ Unlike other models of introspection that are based on "best-response" dynamics, the model we consider here explains choices that move "away" from equilibrium despite common knowledge of the advice. In other words, even after all players know that all know what the "advised claim" is, choices move away from the direction predicted by "best response" behavior.

The next section is briefly devoted to the explanation of the traveler's dilemma game. Section 3 introduces our model and section 4 presents the simulations. The experimental design and procedures are presented in section 5. In section 6 the

³ Goeree and Holt (2004) also introduce a model of noisy introspection. It is a two-parameter model, one (the error parameter) that measures the deviation from the best response, another (the telescoping parameter) that discounts thought iterations.

⁴ The p -beauty contest game is also adequate for the evaluation of "reasoning chains." In this game, players are asked to choose a number between 100 and 0. The choice closest to p ($0 < p < 1$) times the average of all choices wins a prize. This game was analyzed experimentally by Nagel (1995).

⁵ We do not test the predictions against Quantal Response Equilibrium because our model is not an equilibrium model. Our model is designed to test decisions that are not equilibrium decisions.

experimental and simulated data are described and compared with the theoretical predictions. Finally, the last section, section 7, contains the conclusion.

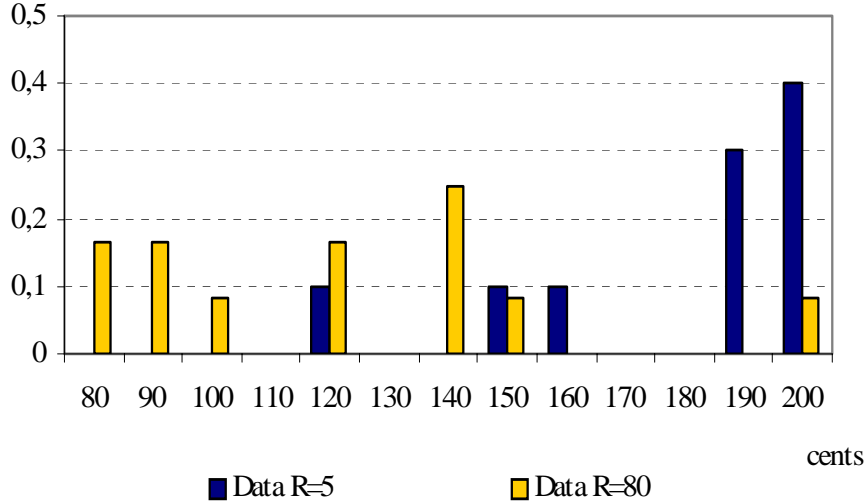
2. The traveler's dilemma

Consider the following story. Two travelers lose their luggage during a flight when returning from a remote island. The luggage of each traveler contains the exact same object. To compensate for the damages, the airline manager asks each traveler to independently make a claim for the value of the lost art between \underline{x} and \bar{x} . And, in an attempt to discourage lying, the manager offers to pay each traveler the minimum of the two claims, plus a reward of r for the lower claimant, minus a penalty of r for the higher claimant. If the claim amounts are the same, each traveler is fully reimbursed for the claim. The Nash equilibrium predicts that both players will make the minimum claim, independent of the size of the penalty or reward because, for any common claim, each traveler has an incentive to “undercut” the other’s claim; the only state where nobody has such incentive to deviate happens when both claims are identical and equal to the minimum amount. In contrast, Capra *et al.* (1999) use data from the last five periods of a multiple periods random-matching traveler’s dilemma game to confirm that players’ behavior is close to the Nash prediction when the penalty or reward is relatively high, but that claims converge away from equilibrium when the penalty or reward is relatively small.

A casual look at Capra et al’s first period data from a traveler’s dilemma game with parameters $\underline{x} = 80$, $\bar{x} = 200$ and low reward/penalty ($r = 5$) or high reward/penalty ($r = 80$), shown in Figure 1, suggests that payoff incentives affect first-period choices in a manner similar to how incentives affect equilibrium choices. We believe that this first-period effect indicates that, before any decision is made, players engage in an introspective type of decision-making process that takes into account payoffs from possible claims and their respective opportunity cost (i.e., penalty/reward).⁶

⁶ However, in this game, players knew that the game will be played a number of periods, thus first period choices are likely to be affected by other factors in addition to payoffs and errors; such factors should disappear in single interaction games.

Figure 1: Observed First-period Claim Frequencies
(Claims are between 80 and 200 cents with penalty/reward of 5 or 80 cents)



Thus, in the section that follows, we derive a prediction of the introspective model for a discrete version of the traveler’s dilemma game presented in Table 1. The claims in this game range between 20 and 120, with a reward/penalty of 5. Notice that in this game the Nash equilibrium prediction is to claim the minimum amount (i.e., 20); a claim of 20 is also the only rationalizable equilibrium.⁷

⁷ The concept of rationalizability is entirely derived from the assumptions of rationality and common knowledge of rationality. A rational player will only use those strategies that are best responses to some beliefs about the opponents’ strategies. In addition, a player should also be able to construct a conjecture of the other’s assessment of that player’s own action for which the initial forecast is a best response. This process of applying best responses to best responses happens in the player’s mind; hence, rationalizability requires a kind of introspective process to find a solution. Applied to the traveler’s dilemma in Figure 1, the process to find a rationalizable solution may go as follows: Row player would exclude playing the maximum claim of 120 cents because the choice of a claim $k=120$ has zero probability of happening. It is not a best reply to any strategy. Moreover, since rationality is common knowledge, Row should expect Column to exclude 120 cents as well; hence, Row should not choose 119 since this claim is not a best response to a belief that happens with positive probability. And, since rationality is common knowledge, Row should not expect Column to choose 119, and so on. 20 cents is the only strategy that survives all possible rounds of iterations of best responses.

Table 1: The Traveler's Dilemma in Normal Form
 (claims are between 20 and 120 cents with reward/penalty of 5 cents)
 * Nash equilibrium/ rationalizable equilibrium

		Column Player							
		k=20	k=21	k=22	k=23	k=119	k=120
Row Player	k=20	20, 20*	25, 15	25, 15	25, 15	25, 15	25, 15
	k=21	15, 25	21, 21	26, 16	26, 16	26, 16	26, 16
	k=22	15, 25	16, 26	22, 22	21, 11	21, 11	21, 11
	k=23	15, 25	16, 26	11, 21	23, 23	22, 12	22, 12
	k=24	15, 25	16, 26	11, 21	12, 22	29, 19	29, 19

	k=119	15, 25	16, 26	11, 21	12, 22	119, 119	114, 124
	k=120	15, 25	16, 26	11, 21	12, 22	114, 124	120, 120

3. The introspective model

To illustrate the way this model works, consider the 2x2 game of Table 2. In order to make a clearer distinction between player 1's choices and player 2's choices, we will call player 1 "he" and player 2 "she." Figure 2 depicts the introspective process for the game in Table 2. Up is U, Down is D, Left is L and Right is R.

Table 2: A Simple 2x2 Game

		Player 2 (she)	
		Left	Right
Player 1 (he)	Up	a ₁ , a ₂	b ₁ , c ₂
	Down	c ₁ , b ₂	d ₁ , d ₂

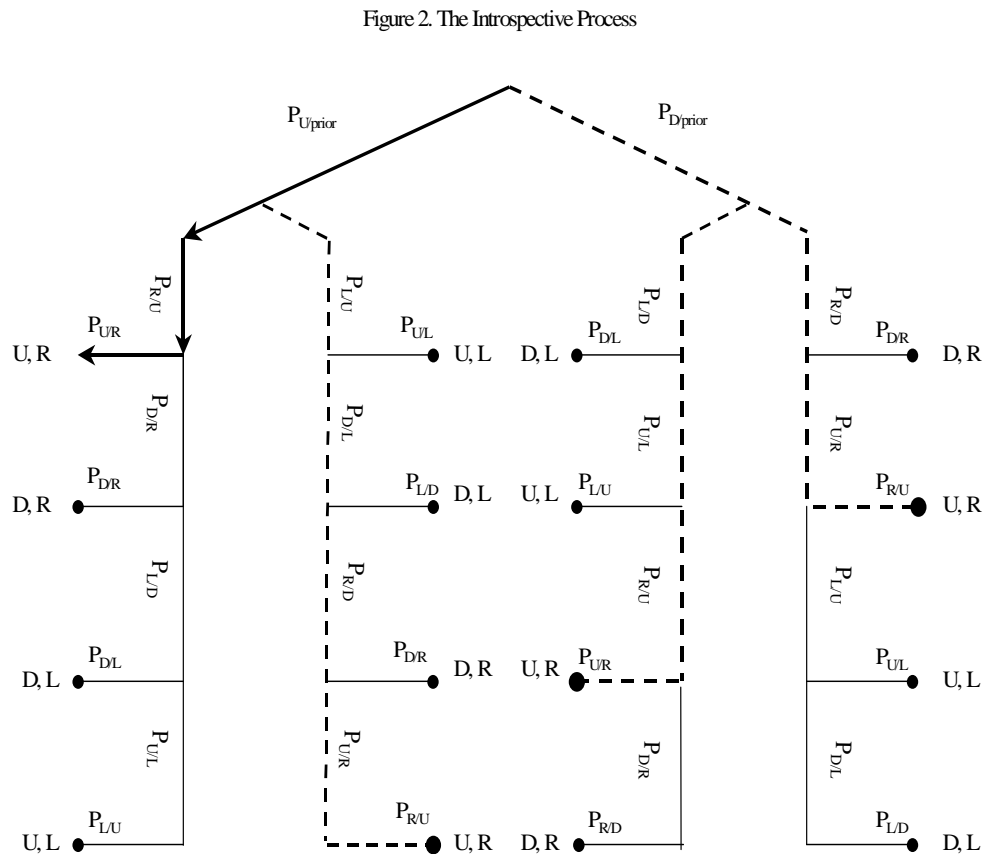
3.2. Finding a Solution

The tree in Figure 2 will help us depict the process by which player 1 reaches a conclusion of what to do. The tree is composed of branches and end-nodes. The branches describe the conditional probabilities of choosing different actions given a believe he or she has about the other's actions. The end-nodes represent the possible strategy combinations at which the thinking process can stop (i.e., (Up, Left), (Up, Right), (Down, Left), and (Down, Right)).

The solution to this model requires following the iterative process step by step. Let σ^2 be player 1's initial subjective "initial" belief or prior that player 2 will choose Left (L).⁸ The probability that player 1 will think that Up (U) is the "best thing to do" is given by $P_{U|\sigma^2}$ and follows the logit rule:

$$P_{U|\sigma^2} = \frac{\exp(\frac{1}{\mu}(\sigma^2 a_1 + (1 - \sigma^2) b_1))}{\exp(\frac{1}{\mu}(\sigma^2 a_1 + (1 - \sigma^2) b_1)) + \exp(\frac{1}{\mu}(\sigma^2 c_1 + (1 - \sigma^2) d_1))}$$

Figure 2. The introspective process



The above probability represents player 1's stochastic response to an initial belief and it means that with probability $P_{U|\sigma^2}$ he will think that he should definitely (for sure)

⁸ The initial beliefs represent the starting point of the introspective process.

choose Up. To determine what player 2 does, he would calculate player 2's response to a belief that he should, indeed, choose Up (belief probabilities are always 1 or zero).⁹ By dividing by the numerator, the expression above equals,

$$P_{U|\sigma^2} = \frac{1}{1 + \exp(\frac{1}{\mu}(\sigma^2(c_1 - a_1) + (1 - \sigma^2)(d_1 - b_1)))}$$

On the other hand,

$$P_{D|\sigma^2} = \frac{1}{1 + \exp(\frac{1}{\mu}(\sigma^2(a_1 - c_1) + (1 - \sigma^2)(b_1 - d_1)))} = 1 - P_{U|\sigma^2}$$

is the probability that player 1 will think that Down (D) is a best reply to the initial beliefs about 2's actions. Suppose player 1 thinks that he should choose Up (U), the first bold arrow on the far-left branch of the thinking tree represents this "move." Then, player 1 forms an expectation of what the other would do by calculating the other's response given that he chooses Up (U). Will player 2 choose Left (L) or Right (R)?

Suppose that player 1 predicts that player 2 will choose Right as a response of him choosing Up; this happens with probability,

$$P_{R|U} = \frac{1}{1 + \exp(\frac{1}{\mu}(a_2 - c_2))}$$

and is represented by the bold arrow pointing down. Then, player 1 calculates his new response following his prediction that the other would choose Right. With probability,

$$P_{D|R} = \frac{1}{1 + \exp(\frac{1}{\mu}(b_1 - d_1))}$$

he will think that given that player 2 will choose Right, he should choose Down. The non-bold arrow pointing down on the far-left-branch of the tree represents this "move." Conversely, with probability,

$$P_{U|R} = \frac{1}{1 + \exp(\frac{1}{\mu}(d_1 - b_1))}$$

he will think that Up is better. Suppose that he decides for Up, the third bold arrow pointing to the left represents this "move." If this happens, the stopping rule is satisfied.¹⁰ That is, given the other is expected to choose Right, he would like to choose Up, and given that he

⁹ In this model beliefs are degenerate distributions that put all the probability mass at one point.

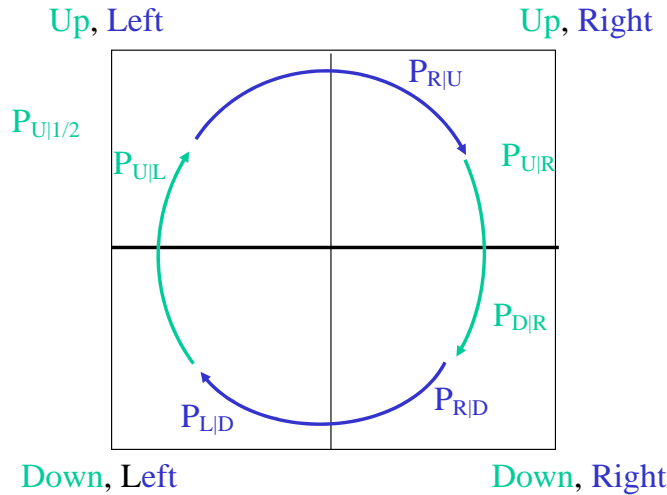
¹⁰ The stopping rule requires a linked pair of stochastic responses.

thinks the rival expects him to choose Up, he thinks the rival would want to choose Right. Player 1, then, stops thinking and infers the strategy pair $(Up, Right)$ should be the outcome of the game. From an observer's point of view, the probability that player 1 will infer the strategy pair $(Up, Right)$ is the solution of this game is given by $P_{U|\sigma^2} P_{R|U} P_{U|R}$.

In Figure 2, there are four branches that lead to the end-node $(Up, Right)$. Consider the left-hand branches in bold; the probability that player 1 thinks $(Up, Right)$ is the outcome of the game (on the first thought iteration) is equal to the product of the probabilities of being in each of the three branches. Likewise, there are three other ways by which $(Up, Right)$ could be reached in the first cycle, as is represented by the bold-dashed lines on the tree.

However, it could be that the process does not stop at any node on the first round, but the player continues iterating (or cycling around a branch). Let Ω represent a complete cycle around the far-left branch of the tree without stopping at any of the four end-nodes, $\Omega = P_{R|U} P_{D|R} P_{L|D} P_{U|L}$. Let n be the number of complete cycles; that is, the number of times the process cycles around all four end-nodes without stopping. Figure 3 depicts the cycle just described.

Figure 3: Clockwise circle: $\Omega = P_{R|U} P_{D|R} P_{L|D} P_{U|L}$

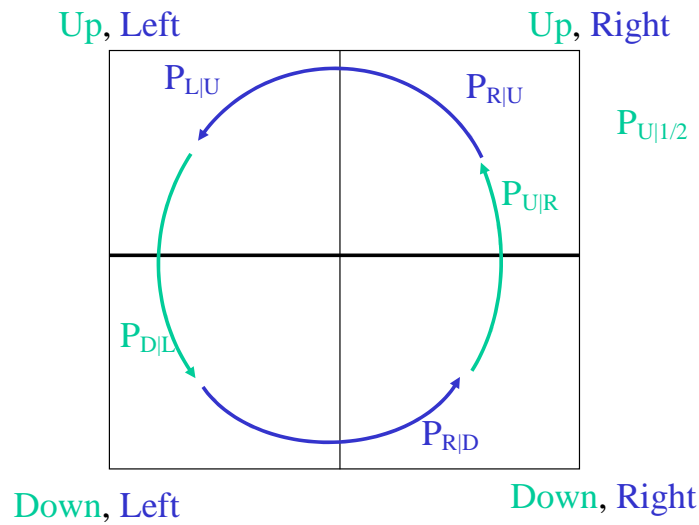


Now, suppose that the thought process does not stop at $(Up, Right)$ on the first cycle, but stops there on the second cycle. Then, the probability of stopping at the $(Up, Right)$ end-node in two cycles is equal to the following sum: $P_{U|\sigma^2} P_{R|U} P_{U|R} (1 + \Omega)$.

Following this same line of reasoning, as the number of complete cycles, n , goes to infinity, the probability of ending up in $(Up, Right)$ when we are on the far-left branch of the tree of Figure 2 is equal to the following sum: $P_{U|\sigma^2} P_{R|U} P_{U|R} \sum_{n=0}^{\infty} (\Omega)^n$. Finally, when one considers *all* possible ways (the one just discussed and the other three represented by the dashed lines in Figure 2) of reaching the end-node $(Up, Right)$, one can calculate the probability with which player 1 reaches the conclusion that he should choose Up and the other should choose Right.

Define $Q^{(U,R)}$ to be the probability that the introspective process will lead player 1 to believe that $(Up, Right)$ is the solution of the game. In addition, let Γ represent a complete cycle on the centre-left branch or the far right branch of the tree of Figure 2. That is, $\Gamma = P_{L|U} P_{D|L} P_{R|D} P_{U|R}$. The cycle Ω can be thought of being a clockwise cycle, while Γ is a counter-clockwise cycle. More specifically, the cycle will be equal to Ω when the process moves from $P_{U|\sigma}$ to a response $P_{R|U}$, or from $P_{D|\sigma}$ to a response $P_{L|D}$, respectively. Conversely, the cycle will equal Γ when the process moves from $P_{U|\sigma}$ to $P_{L|U}$, or from $P_{D|\sigma}$ to $P_{R|D}$. This cycle is depicted in Figure 4.

Figure 4: Counter-clockwise cycle: $\Gamma = P_{L|U} P_{D|L} P_{R|D} P_{U|R}$



Considering all possible ways of getting to $(Up, Right)$, the probability $Q^{(U,R)}$ is then equal to the following expression:

$$Q^{(U,R)} = P_{U|\sigma^2} P_{R|U} P_{U|R} \sum_{n=0}^{\infty} (\Omega)^n + P_{U|\sigma^2} P_{L|U} P_{D|L} P_{R|D} P_{U|R} P_{R|U} \sum_{n=0}^{\infty} (\Gamma)^n \\ + P_{D|\sigma^2} P_{L|D} P_{U|L} P_{R|U} P_{U|R} \sum_{n=0}^{\infty} (\Omega)^n + P_{D|\sigma^2} P_{R|D} P_{U|R} P_{R|U} \sum_{n=0}^{\infty} (\Gamma)^n$$

Note that this is an infinite geometric series that converges to the expressions below:

$$Q^{(U,R)} = P_{U|\sigma^2} \left(\frac{P_{R|U} P_{U|R}}{1-\Omega} + \frac{\Gamma P_{R|U}}{1-\Gamma} \right) + P_{D|\sigma^2} \left(\frac{P_{R|D} P_{U|R} P_{R|U}}{1-\Gamma} + \frac{P_{L|D} P_{U|L} P_{R|U} P_{U|R}}{1-\Omega} \right)$$

In a similar manner, we can calculate the probabilities of ending up in any of the other nodes. Appendix 1 shows these probabilities.

3.2. *Properties of the Introspective Model*

Capra (1999) shows that, when the error parameter goes to infinity (random behavior), each strategy combination or end-node is reached with equal probability of $1/4$ and each strategy is played with equal probability of $1/2$.¹¹ Conversely, as the error parameter goes to zero (perfect rationality), the probability of selecting a Nash equilibrium approaches one.¹²

3.3. *Numerical Example*

The results of numerical examples are interesting because they can be compared with empirical data from laboratory experiments. Consider, for example, the symmetric battle-of-the-sexes game described in Table 3. Cooper *et al.* (1989) and Straub (1995) present experimental results for battle-of-the-sexes games with payoff matrices similar to those of this table.¹³

¹¹ Intuitively, the overall probability that a player's decision process stops at an end-node depends on the product of the conditional probabilities. When $\mu \rightarrow \infty$ all these probabilities equal $1/2$; hence, by replacing the conditional probabilities with $1/2$, it is straightforward to see that $\lim_{\mu \rightarrow \infty} Q^{(U,R)} = \lim_{\mu \rightarrow \infty} Q^{(U,L)} = \lim_{\mu \rightarrow \infty} Q^{(D,R)} = \lim_{\mu \rightarrow \infty} Q^{(D,L)} \rightarrow 1/4$.

¹² Probabilistic responses become best responses, the stopping rule is the consistency condition, and there is no iteration.

¹³ Instead of payoffs of 6 and 2, Cooper *et al.* (1989) use 600 and 200 and Straub (1995) uses 60 and 20.

Table 3: A Numerical Example: The Battle of the Sexes Game

		Player 2	
		L	R
Player 1	U	0, 0	6, 2
	D	2, 6	0, 0

For the game of Table 3, the experimental results of Cooper *et al.* (1989) show that the strategies D and R were played 63 percent of the time compared to the mixed-strategy solution frequency of 75 percent. Moreover, one of Straub's (1995) data for the same game shows that the D and R strategies were chosen 60.56 percent of the time.¹⁴ For a calibrated error parameter of $\mu=2.5$, our introspective process predicts that the D and R strategy choices will be played 62.58 percent of the time, almost the exact same percentage observed experimentally by Cooper *et al.* (1989) and Straub (1995).

3.4. Starting Point of the Introspective Process

The thinking tree of Figure 2 starts at an initial node that describes the initial prior probabilities. It is reasonable to expect that, initially, players have uniformly distributed priors, reflecting total uncertainty about what the other would do, and by the introspective model these uniform prior beliefs are then reassessed. However, there is an argument for considering other initial prior probabilities. Although the values of the starting belief probabilities do not affect the fact that there is a unique outcome in this process and that its properties are intuitive, they affect what the solution itself would be. In some contexts, players' initial beliefs may be affected by salient strategies that attract the attention of the players by virtue of their position, payoffs, or some other aspect (see Schelling, 1960).

Some experimental research attempts to test whether salient strategies are used in coordination games (see Cooper *et al.*, 1993, Van Huyck *et al.*, 1990, and Mehta *et al.*,

¹⁴ These data represent the aggregate frequency of D and R choices for the game played several times. However, the one-shot structure of the game was kept in the experiments by matching each player against a different anonymous opponent in each period. In these experiments, no player knew the identity of the player he was matched with or the history of decisions made by any of the other players. Nevertheless, these data do not necessarily equal those would come from a purely one-shot experiment, where repetition and learning are not allowed.

1994). Since it is reasonable to conjecture that salience may resolve coordination, it is natural to test this hypothesis in a laboratory context. Indeed, the results of Mehta *et al.* (1994) for behavior in two-person coordination experiments suggest that players sometimes coordinate by picking the strategy that is salient, but more often they “reason further” and would choose the strategy that is a best response to the focal point.¹⁵

Applied to the single interaction traveler’s dilemma game, we would expect initial beliefs to be uniformly distributed over all possible strategies. In contrast, when advice is introduced, we should expect the introspective process to begin at the advice—advice is salient and it is common knowledge—. The next two sections depict the results of the simulations for each of the games we analyzed: 1) repeated traveler’s dilemma game, 2) single interaction traveler’s dilemma game, 3) single interaction traveler’s dilemma game with high claim advice, and 4) single interaction traveler’s dilemma game with low claim advice. The reason why advice is analyzed is twofold; first, we can test the robustness of the introspective model by comparing the theoretical predictions with varying starting points to the experimental observations. Second, we can compare our model to other models of introspection that are based on “best response” dynamics such as n-level rationality.

4. Simulations

In a game played by two players, with two strategies each such as the game described above or in Capra (1999), one can find an analytical solution of the introspective process; however, when the number of strategies exceeds two, tracing the probabilistic responses analytically becomes very complex.¹⁶ Complexity, in a way, can justify the use

¹⁵ According to Mehta *et al.*, the subjects who reason further have a depth of reasoning of order n . If a strategy is chosen that is the best response to a salient point, the order of the depth of reasoning is 1. Similarly, if one uses a strategy that is a best response of a best response to the salient point, the depth of reasoning has order 2, etc. Camerer, et al. (2003) estimate the distribution of players’ types based on their depths of reasoning or cognitive sophistication. For a wide range of one-shot games, players’ cognitive sophistication in terms of how many times they apply best responses follow a Poisson distribution with mean depth of reasoning between 1 and 2.

¹⁶ As mentioned above, for a two-player/two-strategies simultaneous game, when the introspective process stops after one cycle, there is one clockwise “cyclical” way in which the same end-node can be reached (see Figure 3). For a two-player/three-strategies game, when the thought process stops after one cycle, there are four possible clockwise cyclical ways that the same end-node can be reached. In the same manner, for a two

of simulations to find a prediction of the introspective process for a discrete version of the traveler's dilemma, which in our example has 101 strategies for each player.¹⁷

A detailed copy of the program that was used to run the simulations can be found at the following web site (<http://userwww.service.emory.edu/~mcapra/papers.html>). The procedures that make up the program are shown below. The simulation for the no-advice game was done assuming that the initial probabilities (the point at which the thought process starts) are flat rather than salient. For the advice treatments, we took the advice as the point of departure for the introspective process.

```

Begin {main Program}
  Initialize;
  FOR t := 1 TO number_of_terminations DO
  BEGIN {Begin tracing number, t}
    Initialize_tracing;
    While (Convergence = FALSE) DO
      Begin {Introspective process}
        Calculate_expected_payoffs;
        Calculate_decision_probabilities;
        Calculate_beliefs;
        Check_convergence; {stopping rule}
      End; {end Introspective process}
    Record_end_node;
  END; {end tracing}
End. {end main program}

```

A total of 30 iterations were done for Traveler's Dilemma games with different starting point. When the stopping rule was satisfied, a count was recorded in one of the 10,201 (101x101) strategy combinations or end-nodes. For the simulations, the value of the error parameter, μ , was different; higher for the no-advice and low-advice treatments and lower for the high-advice treatment. In the first two cases, we used an error term equal to one estimated by Capra (1999) for other one-shot games. For the high-advice treatment, we used an error parameter equal to the one estimated by Capra *et al.* (1999) for the repeated traveler's dilemma game (explanation for these choices are provided in the next section).

player game with n possible strategies, there are $2 \sum_{i=2}^n [2(i-1) - 1]$ cycles (clockwise and counterclockwise) that lead to the same end node.

¹⁷ The discrete version of the Traveler's Dilemma is shown in Table 1.

In section 6, we analyze the results of the simulations and compare them to the experimental observations.

5. Experimental Design and Procedures

We organized an experiment to test the prediction and robustness of our model. As mentioned above, there are two reasons why we decided to test for the effects of advice on decisions. To begin, a common advice, should lead to lower claims if people's behavior is best described by models of introspection that use best responses such as n-level rationality or cognitive hierarchies. Such lower claims are not expected if people's behavior is best described by our model of introspection, since our model uses probabilistic responses. Thus, a one-shot traveler's dilemma game with common advice should help us compare the predictive power of the "competing" models of introspection. Secondly, a common advice can test the robustness of the model to changes in the starting point or departure of the process.¹⁸

Participants in our experiment were recruited from a variety of economics courses at the University of Malaga in Spain. Subjects were paid 500 pesetas (about \$3.00) for showing up, and during the experiment they made on average 1,318 pesetas (about \$8.00).¹⁹ Instructions were written in Spanish and read aloud. We designed an experiment that consisted of one repeated interaction traveler's dilemma game and three cells of single interaction (one-shot) traveler's dilemma games. The three one-shot treatments were no-advice (control), low-advice, and high-advice. The repeated game session lasted about one hour, whereas the other sessions lasted about 30 minutes each. Each session had 10 subjects and no single subject participated in more than one session. We organized three sessions under each one-shot treatment and each cell or set of sessions with identical treatment was administered simultaneously to avoid rumors (see Table 4). In all treatments, subjects were asked to choose a claim between and including 20 and 120; they were told that the earnings

¹⁸ On a more informal way, we are also interested in seeing the effects of advice because many real life situations decision-makers do not have the opportunity to repeat their choices under constant external conditions (i.e., "Groundhog Day"). Nevertheless, any decision-maker that faces a single interaction game (i.e., auction, voting, or war) is likely to ask for advice.

¹⁹ Subjects who participated in the repeated interaction session made on average 1,364 pesetas. Subjects who participated in the single interaction games made on average 1,271 pesetas. Payoffs were in tokens with a conversion rate of 1 to 2 pesetas for the repeated game and 1 to 10 pesetas for the one-shot games.

would depend on their decisions and the decisions made by the persons randomly matched with them. The reward/penalty parameter for all sessions was equal to 5. Table 4 below summarizes the experimental design.

Table 4: Summary of Experimental Design

Session	# of subjects per session	# of subjects per treatment	# of periods	Treatment	
1	10	10	10	Repeated TD	Subjects were asked to give advice } Parallel sessions
2, 3, 4	10	30	1	One-shot TD with no advice	
5, 6, 7	10	30	1	One-shot TD w High claim advice	
8, 9, 10	10	30	1	One-shot TD w Low claim advice	

In the repeated traveler’s dilemma game session, participants interacted for 10 periods and in each period they were randomly matched with someone else in the room. At the end of the experiment, they were told to give advice to subjects who were going to play the exact same game, but only once (see the translated instructions in Appendix 2).

In the single interaction sessions, participants were told that they had to make a single claim between and including 20 and 120 and that their earnings would depend on their choice and the choice made by someone else in the room (randomly chosen). In the low-advice and high-advice treatments, they were also given the following information:

...Other students, who showed high interest and motivation in this exercise, participated in this experiment before you. They had the advantage of being able to make decisions ten times; you are going to play only once. After they made their tenth decision, we asked them to give advice about which number someone who is playing only once should choose. This was one of the advices given: “the best number that you could choose is ____”. You should keep in mind that you can choose any number that you want; that is, you are free to take or dismiss this advice.

The advice given by subjects who played repeated game ranged from 120 to 24. We selected an advice of 119 (given by two participants) as the high-advice and an advice of 79 as the low-advice (given by one participant).²⁰

6. Experimental Results

The observed and simulated choices for each claim amount are provided in Appendix 3. Figures 5 show the relative frequencies of choices for each one-shot condition, separately. The medians, modes and means are also shown in this figure. No subject chose numbers below 45 in the advice sessions and only five subjects chose claims below 45 in the no advice sessions (16.6 percent)²¹. A casual look at this figure suggests that there is a much higher dispersion in the no-advice treatment than in the other two treatments, which is consistent with more varied starting points across subjects, as we predict. Claims in the no-advice treatment spread on the full range of numbers. However, choices between 110 and 120 are the most selected; 11 people out of 30 (i.e., 36.7%) selected a number in that interval. Dividing the range of choices into three and matching choices to each third of the range, six subjects chose numbers in the first third, seven subjects in the second third, and seventeen people in the higher third.

When a low-advice of 79 was provided, most subjects chose numbers between 110 and 120 (eight people out of 30), but an equal number of subjects choose numbers between 60 and 70. Seventeen people out of 30 selected a number higher than 79. No subject chose the number advised. Dividing the range of possible choices in three thirds, we can see that people selected numbers in the middle or last third of the range: one subject out of 30 selected a number in the first third (3.3%), sixteen in the second third (53.3%), and thirteen in the last third (43.3%). When the advice offered to subjects is high, most people (nineteen out of 30 or 63.3% of subjects) choose a number between 110 and 120. Dividing the range of numbers in three parts, we can see that most people choose high numbers or those belonging to the last third of the range. One person selected a number in the first third of the range (3.3%), four people in the second (13.3%), and 25 in the last third (83.3%).

²⁰ The advised claims given by the participants in the repeated game session were 120, 119, 119, 100, 100, 95, 79, 30, 25, and 24. We chose 119 because it is the highest advice less than the maximum of 200. We chose 79 because it is closer to the mean, 70, which we believed was salient.

²¹ In the no advice sessions, only one subject chose 20 (the equilibrium strategy).

In the extreme case of bounded rationality, subjects would take decisions at random and any number between 20 and 120 would be equally likely to be selected. In order to see whether subjects behave at random or follow some other more specific pattern of behavior, we used a Kolmogorov-Smirnov one-sample test of goodness-of-fit. The test is concerned with the degree of agreement between the distribution of a set of sample values (observed claims) and some specified theoretical distribution, which will be the uniform distribution in this case. We can reject the null hypotheses that the data follow a uniform distribution at a 0.01 level of significance (α) for the high and low-advice sessions; and for the no advice session at $\alpha = 0.05$.²²

Once we conclude that subjects do not behave at random, we are concerned with the possible treatment effects. We use the Wilcoxon-Mann-Whitney test for large samples, which is one of the most powerful of the nonparametric tests. According to it, we can reject the null hypothesis that the data from the high and low-advice sessions are drawn from the same distribution, against the alternative hypothesis that population in the high-advice sessions is stochastically larger, i.e. most of the numbers chosen in the high-advice sessions are higher, at a 0.01 level of significance (z-value = -2.5134). The same result holds for a test of the data from the high-advice and no advice sessions (i.e., claims selected are higher in the high-advice sessions than in the low-advice sessions (z-value= -2.0920). However, the null hypothesis that the data from the low-advice and no advice sessions are equal cannot be rejected at $\alpha=0.05$ (z-value = -0.0183).²³

We can use the data to test whether choices exhibit the structure suggested by models of introspection that are based on best response dynamics such as n-level rationality. When no advice is given to subjects, a player would be strategic of degree 0, (a player has a depth of reasoning of order 0, if he chooses the number 70 (the midpoint of the

²² The maximum deviations were 0.533, 0.3 and 0.267 for the high-advice, low-advice and no advice cases respectively. The critical value of the maximum deviation for 30 observations at a 0.01 level of significance is 0.29. An alternative test to the Kolmogorov-Smirnov one-sample goodness-of-fit test is the chi-square test. When samples are large, either of them could be applied. However, with small samples, the Kolmogorov-Smirnov test is more powerful than the chi-square test. See Siegel and Castellan (1988) for details.

²³ An alternative test to the Wilcoxon-Mann-Whitney test is the Kolmogorov-Smirnov two-sample one-tailed test. However, whereas for very small samples the Kolmogorov-Smirnov test is slightly more efficient than the Wilcoxon-Mann-Whitney test, for large samples the converse holds. Anyways, for comparing the low-advice and no-advice sessions, we used the Kolmogorov-Smirnov two-tailed test for large numbers with the null hypothesis that the claims observed follow the same distribution. We were unable to reject the null hypothesis of no difference at $\alpha=0.05$ ($D=1.67$, $df=1$).

interval [20; 120]). This can be interpreted as the expected choice of a player who chooses randomly from a uniform distribution or a salient number according to Schelling (1960). A player would be strategic of degree 1, if he chooses a number that is the best response to the number 70. A person has a depth of reasoning of order 2, if he chooses a number that is the best response to the best response of 70, etc. Similarly, when subjects are provided with an advice and that advice is common knowledge, the focal point of 70 would be replaced with the number advised. According to this model of behavior, the main feature of empirical frequencies is that most choices would be concentrated below the focal point. However, in the no-advice sessions 70% of the subjects chose a number higher than 70; and in the low-advice sessions, 56.6% chose a number higher than 79. It is obvious that n-level rationality does not explain data from these sessions. Indeed, in the high-advice sessions, only 6.7% of the subjects chose a number higher than 119; 6.7% chose the advice given; 20% chose numbers in the interval [118; 119); and 6.7% selected numbers belonging to the interval [117; 118). Then, in the high-advice sessions, only 33.4% of the subjects behave consistently with depths of reasoning of orders 0, 1 or 2.²⁴

Once we reach the result that neither rationalizability (which predicts the minimum claim) nor n-level rationality explains the data, our introspective process for a discrete version of the traveler's dilemma is simulated using the advice as the focal or salient departure point. For the no-advice simulation, we use uniformly distributed initial conditions. Error decision parameters do not have to be equal in the three cases considered. However, we do not calibrate the model. That is, our data is not used to find maximum likelihood estimates of the decision error due to unavailability of data. Regardless, the amount of noise in the data should depend on the subject pool, the complexity of the game, the experience of subjects, and the importance of "un-modeled" factors in the decision-making process.

We assume that the size of the error parameter would be lower when the advice is high than when the advice is low or when there is no advice. In fact, when the advice given to the subjects is 119, people would think that this is a very good advice because it allows obtaining high payoffs if they believe others will follow it (or stay close to 119). In a way,

²⁴ The experimental studies in which n-level rationality has been tested support depths of reasoning of orders 0, 1 or 2. See, for instance, Mehta *et al.* (1994), Nagel (1995), and Camerer, *et al.* (2003).

providing an advice of 119 could be a substitute for experience in this game; consequently, we selected a low error parameter, $\mu=8$, which had been roughly the error parameter estimate for the equilibrium model using data from a traveler's dilemma experiment in a previous paper.²⁵

However, when a low-advice is provided, subjects do not confirm their expectations about how the game should be played in order to obtain high payoffs. Thus, we selected a higher error parameter, $\mu=22$, for the low and no advice cases.²⁶ In order to see how the laboratory data fit the simulated data, we applied a Kolmogorov-Smirnov one-sample goodness-of-fit test. As a result, we cannot reject the null hypotheses that data follow the theoretical distributions at the 0.01 level of significance. The maximum deviations were 0.1, 0.2 and 0.267 for the high-advice, low-advice and no-advice cases, respectively.²⁷ Figures 6 show the empirical and simulated distributions for the three cases considered.²⁸ Finally, the simulated number of choices per claim can be found in the following web-site <http://userwww.service.emory.edu/~mcapra/papers.html>.

7. Conclusion

In games played once, there is no chance for repetition or observation of others' actions; hence, arriving at an outcome requires agents to solve the game through some *introspective* process that consists of tracing through a series of responses without feedback from previous plays of the game. In this paper, we introduce a model of introspection that traces the decision-making process to find a prediction of games played once. In our model, players are assumed to trace through responses until a stopping rule is satisfied. The beliefs that determine response probabilities are degenerate distributions that put all of the

²⁵ Capra *et al.* (1999), for data from a Traveler's Dilemma experiment, estimate an error parameter of 8.3 for the equilibrium model and of 10.9 for the dynamic model. Capra *et al.* (2002) obtain an error parameter of 8.4 in an experimental study of imperfect price competition. The estimates for the Anderson and Holt (1997) information cascade experiments imply an error parameter of about 12.5. Finally, McKelvey and Palfrey (1998) estimate an error parameter of 10 for an equilibrium model.

²⁶ Note that this μ is higher than all those values obtained in an equilibrium context or in a learning environment. This error parameter was estimated in Capra (1999) using data from one-shot games.

²⁷ Recall that the critical value at the 1 percent significance level ($\alpha = 0.01$) for 30 observations is 0.29.

²⁸ Comparing the simulated data from the high and low-advice treatments, we observe that the maximum deviation between the cumulative frequencies is 0.4, so the null hypothesis of equal distributions can be rejected ($\alpha = 0.01$). For the high and no-advice cases the maximum deviation is 0.567, so the same conclusion can be reached. Finally, the maximum deviation between the cumulative densities for the low and no advice treatments is equal 0.23; that is, the null hypothesis that distributions are equal cannot be rejected at $\alpha = 0.01$.

probability mass into a single point. The response probabilities follow the logit rule. Thus, our model introduces noise in decision making and hence differs from other models similar *in spirit* (i.e., introspective) such as n-level rationality and cognitive hierarchies.

In the empirical part of this paper, we analyze behavior in the context of a single interaction traveler's dilemma game with advice. The traveler's dilemma game was chosen because in this game "reasoning chains" are likely to occur. Advice was introduced to test the robustness of our model and to compare its predictions to predictions of other models similar in spirit but that rely on best responses. We conducted four experimental treatments: one repeated traveler's dilemma game and three one-shot games with identical parameters. After playing the repeated game, subjects provided non-binding advice to other subjects that participated in two of the three one-shot sessions. The three one shot sessions were no advice (control), high claim advice, and low claim advice.

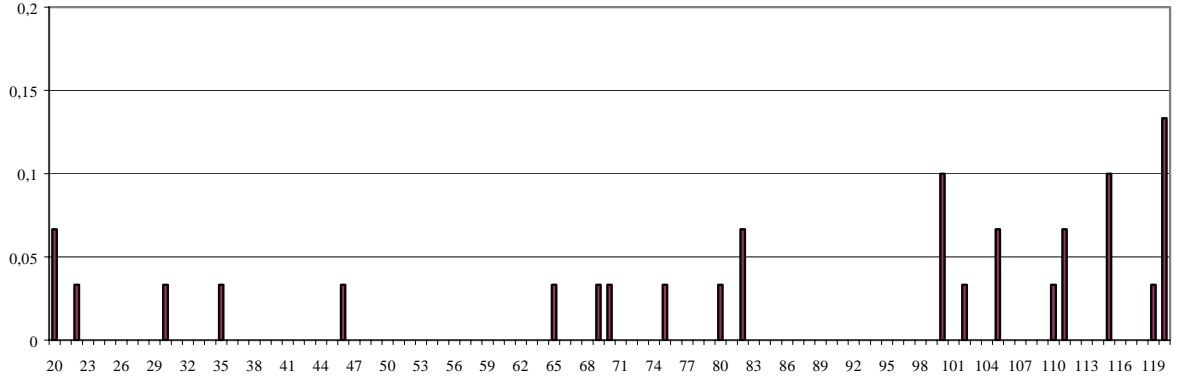
Our results suggest that models of introspection based on best-response dynamics do not explain observed data. Of course, evidence from a single game is not strong enough to put doubt on the validity of n-level rationality or cognitive hierarchies; however, if people do best respond rather than respond with noise, their claims should be below the advice. This is certainly the case for the high-advice treatment, where if all knew that a claim of 119 was advised, best response only leads choices towards one direction: undercut. We did not observe this.

Conversely, our data accurately fit the theoretical distributions provided by simulations of our model and is robust to changes in the initial conditions. Hence, bounded rationality, out-of-equilibrium behavior, decision errors and probabilistic choice seem to be the key ideas to better understand choices made in single interaction games. Finally, we believe that modeling decision processes at the introspective level may not only be relevant for games played only once. These models may help us find a prediction of first period moves in a repeated interaction game. Indeed, most learning models make little attempt to specify initial behavior.

Figures 5. Experimental Frequencies

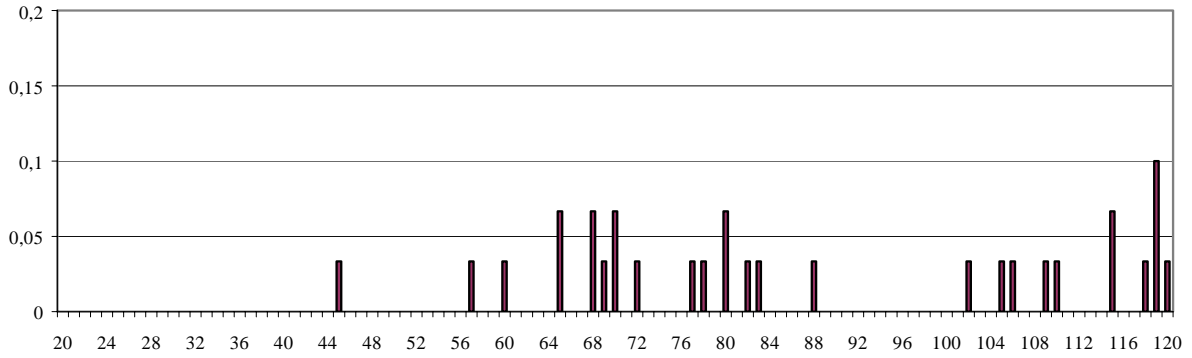
A) No advice

median 100; mode 120; mean 86.21



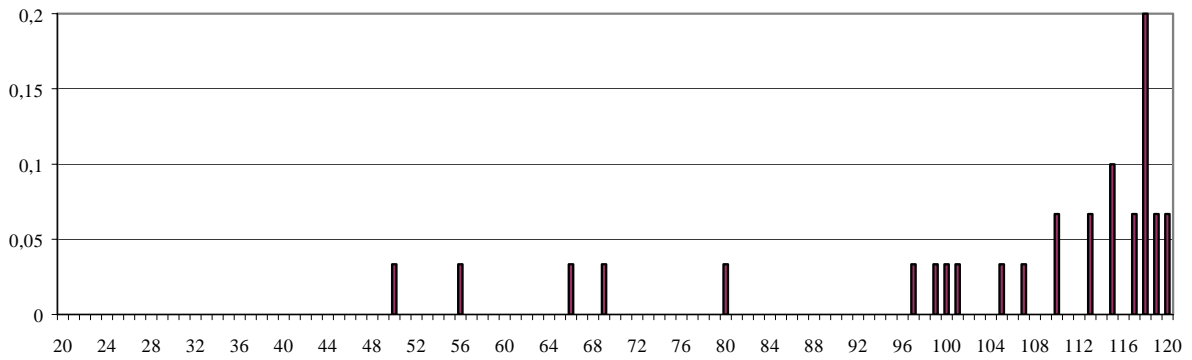
B) Low advice

median 81; mode 119; mean 87.83



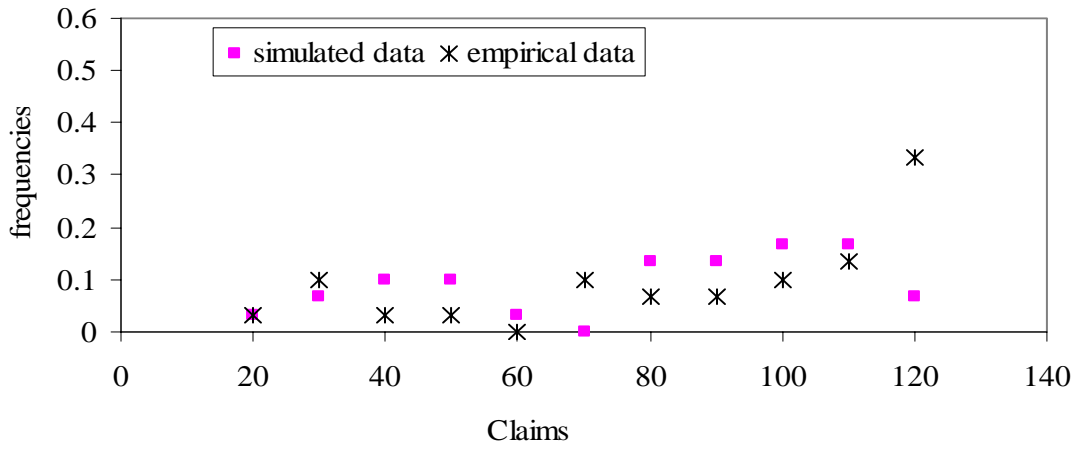
C) High advice

median 114; mode 118; mean 104.81

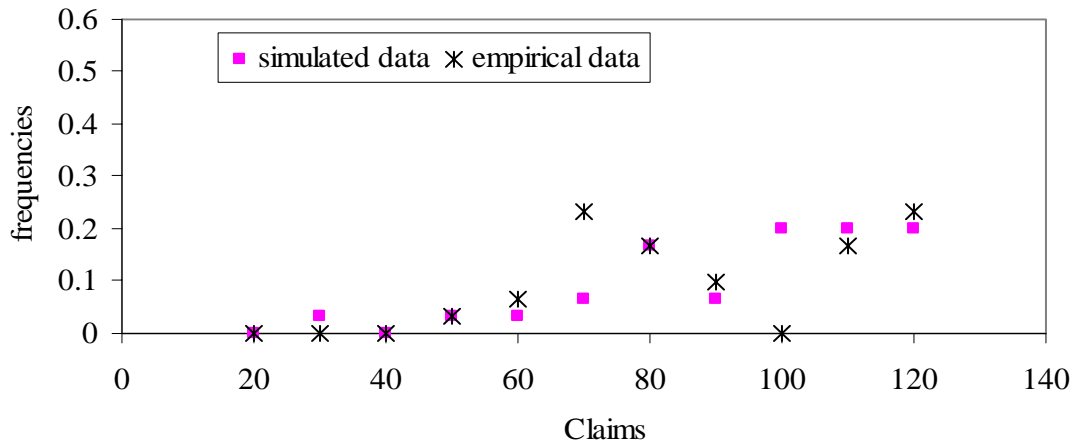


Figures 6: Simulated and Empirical Frequencies

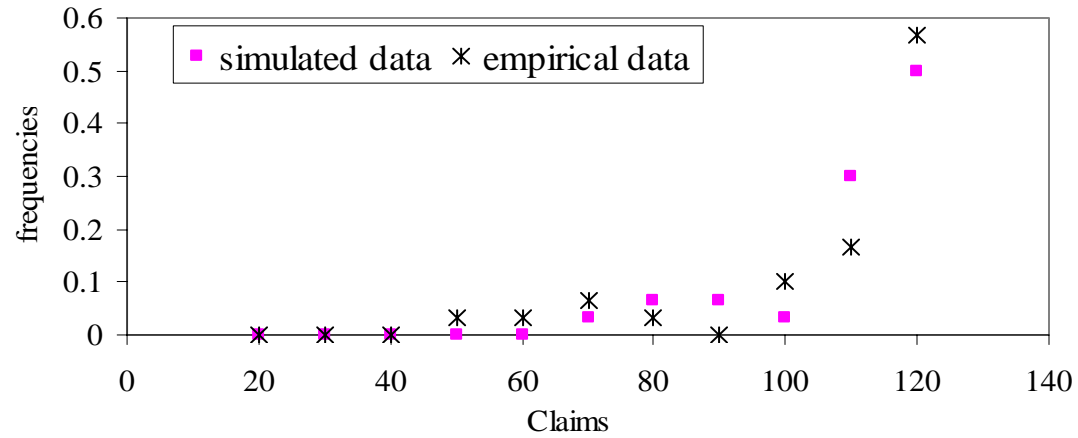
No advice $\mu=22$



Low advice $\mu=22$



High advice $\mu=8$



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APPENDIX 1

For $\Omega = P_{R|U} P_{D|R} P_{L|D} P_{U|L}$, and $\Gamma = P_{L|U} P_{D|L} P_{R|D} P_{U|R}$

$$Q^{(D,L)} = P_{U|\sigma^2} \left(\frac{P_{R|U} P_{D|R} P_{L|D} P_{D|L}}{1-\Omega} + \frac{P_{L|U} P_{D|L} P_{L|D}}{1-\Gamma} \right) + P_{D|\sigma^2} \left(\frac{(\Gamma) P_{L|D}}{1-\Gamma} + \frac{P_{L|D} P_{D|L}}{1-\Omega} \right)$$

$$Q^{(D,R)} = P_{U|\sigma^2} \left(\frac{P_{R|U} P_{D|R} P_{R|D}}{1-\Omega} + \frac{P_{L|U} P_{D|L} P_{R|D} P_{D|R}}{1-\Gamma} \right) + P_{D|\sigma^2} \left(\frac{P_{R|D} P_{D|R}}{1-\Gamma} + \frac{(\Omega) P_{R|D}}{1-\Omega} \right)$$

$$Q^{(U,L)} = P_{U|\sigma^2} \left(\frac{(\Omega) P_{L|U}}{1-\Omega} + \frac{P_{L|U} P_{U|L}}{1-\Gamma} \right) + P_{D|\sigma^2} \left(\frac{P_{R|D} P_{U|R} P_{L|U} P_{U|L}}{1-\Gamma} + \frac{P_{L|D} P_{U|L} P_{L|U}}{1-\Omega} \right)$$

Where:

$$P_{U|L} = \frac{1}{1 + \exp(\frac{1}{\mu}(c_1 - a_1))} \quad P_{U|R} = \frac{1}{1 + \exp(\frac{1}{\mu}(d_1 - b_1))}$$

$$P_{D|L} = \frac{1}{1 + \exp(\frac{1}{\mu}(a_1 - c_1))} \quad P_{D|R} = \frac{1}{1 + \exp(\frac{1}{\mu}(d_1 - b_1))}$$

$$P_{L|U} = \frac{1}{1 + \exp(\frac{1}{\mu}(c_2 - a_2))} \quad P_{L|D} = \frac{1}{1 + \exp(\frac{1}{\mu}(d_2 - b_2))}$$

$$P_{R|U} = \frac{1}{1 + \exp(\frac{1}{\mu}(a_2 - c_2))} \quad P_{R|D} = \frac{1}{1 + \exp(\frac{1}{\mu}(b_2 - d_2))}$$

Note that $P_{D|L} = 1 - P_{U|L}$, $P_{R|U} = 1 - P_{L|U}$, $P_{U|R} = 1 - P_{D|R}$,
and $P_{L|D} = 1 - P_{R|D}$

APPENDIX 2

Your Identification Number _____

Instructions: (translated from Spanish)

You are going to take part in an experimental study of decision making. The funding for this study has been provided by several foundations. The instructions are simple, and by following them carefully, you may earn a considerable amount of money that will be paid to you in cash at the end of this experiment. At this moment, you should have already received some money for showing up. We will start by reading the instructions, and then you will have the opportunity to ask questions about the procedures described.

NOTE: THE FOLLOWING PARAGRAPH WAS INCLUDED IN THE REPEATED TRAVELER'S DILEMMA GAME ONLY

Partners: The experiment consists of a number of periods. In each period, you will be randomly matched with another participant in the room. We will randomly pair you in each period by writing your identification numbers on pieces of paper that we later pick, two at a time. We will take note of the numbers of each pair in each period, but none of you will know the identity of your partners at any moment.

NOTE: THE FOLLOWING PARAGRAPH WAS INCLUDED IN THE ONE-SHOT TRAVELER'S DILEMMA GAMES ONLY

Partners: *Each of you will be randomly matched with another participant in the room. None of you will know the identity of your partners at any moment.*

Decisions: To begin, each of you will choose a number or “claim” between 20 and 120 and write it down on the table below. You can choose any number between and including 20 and 120, with or without decimals. Once you have chosen your number, we will collect your decision and match it in pairs with someone else’s decision.

Earnings: The decisions that you and your partner make will determine the amount earned by each of you. Once we have collected and matched the decision sheets, we will compare the numbers chosen. If the numbers are equal, then you and your partner each receive the amount claimed. If the numbers are not equal, then each of you receives the lower of the two claims. In addition, the person who chooses the lower number earns a reward of 5, and the person with the higher number pays a penalty of 5. Thus, you will earn an amount that equals the lower of the two claims, plus a 5 reward if you are the person making the lower claim, or minus a 5 penalty if you are the person making the higher claim. There is no penalty or reward if the two claims are exactly equal, in which case each person receives what they claimed.

Example: Suppose that your claim is X and the other’s claim is Y .
If $X=Y$, you get X , and the other gets Y .
If $X>Y$, you get Y minus 5, and the other gets Y plus 5.
If $X<Y$, you get X plus 5, and the other gets X minus 5.

NOTE: THE FOLLOWING PART WAS ADDED TO THE ADVICE SESSIONS ONLY

Other students, who showed high interest and motivation in this exercise, participated in this experiment before you. They had the advantage of being able to make decisions ten times; you are going to play only once. After they made their tenth decision, we asked them to give advice about which number someone who is playing only once should choose. This was one of the advices given: *the best number that you could choose is ___*. You should keep in mind that you can choose any number that you want; that is, you are free to take or dismiss this advice.

NOTE: THE FOLLOWING PARTS WERE INCLUDED IN ALL ONE-SHOT SESSIONS

Summary and Record of Results:

Each one of you is matched randomly with another participant in the room. Each one of you is going to write a number between 20 and 120 in the cell of the first column on the table below (in the column called “Your claim”). We will collect all the sheets and we will compare the numbers chosen by each pair of participants. We will write the number chosen by the other participant in the pair, and the earnings (in tokens). Your

earnings in pesetas will be the result of multiplying your earnings in **tokens by 10**. Finally, we will return the decision sheets and then we will pay you privately and in cash the total amount that you earned.

Your claim	The other's claim	Earnings
		A. Your earnings in tokens _____
		B. Your earnings in pesetas _____ = 10*A
		C. Total earnings in pesetas _____ = B + show up money

NOTE: THE FOLLOWING PARTS WERE INCLUDED IN THE REPEATED SESSION ONLY

Summary and Record of Results:

Each period, each one of you is matched randomly with another participant in the room. Each period, each one of you is going to write a number between 20 and 120 in the cell of the first column on the table below (in the column called "Your claim"). We will collect all the sheets and we will compare the numbers chosen by each pair of participants. We will write the number chosen by the other participant in the pair, and the earnings (in tokens). Then, we will return your decision sheets and start a new period by pairing you randomly with someone else in the room. Your earnings in tokens is the sum of the earnings in each period. Your earnings in pesetas will be the result of multiplying your earnings in **tokens by 2**. Finally, we will return de decision sheets and then we will pay you privately and in cash the total amount that you earned.

Period	Your claim	The other's claim	Earnings
1			
2			
....			
10			
			A. Your cumulative earnings in tokens _____
			B. Your earnings in pesetas _____ = 2*A
			C. Total earnings in pesetas _____ = B + show up money

NOTE: THIS SECTION WAS ADDED TO THE REPEATED TRAVELER'S DILEMMA SESSION, AFTER THE 10TH PERIOD

Your identification number _____

Please, answer the next question.

Other students are going to take part in this experiment in the future. The difference is that they are going to play one period only, instead of several periods like you did. You have got some experience that they will not have time to reach. Which number would you recommend they choose? In other words, if you could play this game again tomorrow, but only one period, which number would you choose?

Write your answer here: _____