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Travelers' types☆

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This paper uses subjects' diverse self-reported justifications to explain discrepancies between observed heterogeneous behavior and the unique equilibrium prediction in a one-shot traveler's dilemma experiment. Principal components analysis suggests that iterative reasoning, aspiration levels, competitive behavior, attitudes towards risk and penalties and focal points may be behind different choices. Such reasons are coherent with same subjects' behavior in other tests and experiments in which these particular issues are prominent, and thus, we identify "types" of subjects. Overall, we conclude that subjects' self-justifications in complex strategic situations contain informational value which may be used to predict behavior in other situations of economic importance.

1. Introduction

The traveler's dilemma (TD) is one of the classic examples used to highlight discrepancies between the concept of rationality in Game Theory and the way real individuals take strategic decisions. As such, its intuitive outcome and the game theoretic prediction do not coincide. It was first introduced by Basu (1994) to point out that discrepancies between game theoretic reasoning and actual behavior may not only occur due to problems with backwards induction, as it also may occur in single shot games.[3]

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[3] "The traveler's dilemma seems to be one of the purest embodiments of the paradox of rationality in game theory, because it eschews all unnecessary features, like play over time or the nonstrictness of the equilibrium". (Basu, 1994).

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The original formulation of the TD is as follows:

> "Two travelers lose their luggage during a flight. Each travelers' luggage contains exactly the same object. To compensate for damages, the airline manager asks each traveler to independently make a claim for the value of the lost object between $\underline{b}$ and $\bar{b}$. To discourage false claims, the manager offers to pay each traveler the minimum of the two claims, plus a reward of p to the lowest claimant and minus a penalty of p to the highest claimant."

All standard game theoretic solution concepts predict that both players will select the lowest possible choice $\underline{b}$ and thus, the predicted outcome will be $(\underline{b}, \underline{b})$. This is the unique Nash equilibrium, the unique strict equilibrium, the unique strong equilibrium and the only rationalizable equilibrium. Yet, it seems intuitive that subjects may play differently since, for example, if they believe others will make high claims, choosing higher bs is beneficial for both subjects. Previous experimental evidence (Capra et al., 1999; Goeree and Holt, 2001; Cabrera et al., 2007; Becchetti et al., 2009; Basu et al., forthcoming) shows that a significant proportion of experimental subjects choose values which are higher than the equilibrium prediction and that the size of the penalty (p) influences choices. In particular, lower penalties are associated with higher choices. Becker et al. (2005) show that even a large proportion of experts in Game Theory do not choose according to the Nash prediction when playing an anonymous electronic version of the TD among them. Therefore, ignorance on how to reason in game theoretic terms cannot be the only reason behind the observed heterogeneous choices in TD experiments. Previous theoretical attempts have focused on explaining convergence to the Nash prediction after repeated play in the TD.[4] Since in this paper we are interested in the underlying motivations behind subjects' intuitive and heterogeneous choices, we focus on initial play.[5] Rubinstein (2007), in a one-shot not rewarded TD experiment with an extensive sample, studies subjects' time responses under the hypothesis that more cognitive demanding choices take longer to be taken. Results confirm this hypothesis, although most non-extreme choices remain unexplained. We take a complementary approach too understand heterogeneity in behavior.

In games where the equilibrium prediction holds empirically, individuals' heterogeneity does not play a role. Thus, we focus on a game where players do not play according to the unique equilibrium prediction, the TD, and therefore their choices may reveal the underlying motivations for strategic play. Our main interest in this paper is to use the observed heterogeneity in behavior and in the reasons behind such behavior in order to check consistency among individuals' behavior across strategic and cognitive tasks. Our experiments with the TD can be considered as a first step in this line of research: what are the factors influencing behavior when the Nash prediction is not expected to hold? We search for such factors in players' self-reported motivations and find that the "type of player" (as defined by self-reports) predicts behavior in the TD. We then see whether the identified factors are informative for predicting behavior in different situations. The factors we identify or even their relative weight should not be considered as the definite factors determining behavior until more extensive research has been undertaken, because these factors or their relative weight could be influenced by the design. Further research should reveal whether other factors should be included to define the "type of player" and improve prediction.

We asked for subjects' self-reported justifications of their choices in a version of the TD. This approach is similar to Protocol Analysis, which has proven to be successful in psychological studies.[6] However, a structured use of variables emerging from unpaid questionnaires is far from being standard in economic experiments.[7] We find that not only choices in our TD are heterogeneous, but that alleged reasons behind those different choices in the TD are also consistently heterogeneous. Given such heterogeneity, the TD is an ideal candidate to study different motivations behind subjects' experimental choices. We use independent research assistants to codify subjects' self-reports into variables and we then use principal components analysis (PC) in order to rationalize choices in the TD and classify subjects according to their most prominently alleged reasons. We find that some classic experimental issues such as cognitive complexity, payoff aspirations, social preferences, risk and penalty aversion and focal points are closely related to alleged reasons in our TD experiment.

We also took independent measures of same subjects' personal characteristics and behavior in other tasks and experiments. In particular and with respect to subjects' characteristics, we considered subjects' scores in a GRE-type math test, subjects' self-evaluation in academic activities and gender. With respect to experimental measures, we obtained how much they give in a dictator game experiment and their choices when facing uncertainty in two different tasks. Given the intuitive relationship between subjects' self-reported justifications in the TD and these other measures, we check whether subjects prominently motivated by one particular feature in the TD also score high in the particular task or experiment designed to check such feature. For example, we study whether subjects reporting more cognitively complex reasoning procedures in the TD score high in the GRE-type test or whether subjects using antisocial justifications in the TD give less in dictator games. We obtain coherent and consistent relationships between both types of measures. Overall, we conclude that there exists different types of subjects whose first intuitive responses to a strategic situation are driven by different motivations and that such motivations are relatively consistent across tasks. Therefore, we show that subjects' self-report in strategically complex

[4] For example, Capra et al. (1999) rationalize observed behavior in repeated versions of the game through a learning process in a probabilistic choice model in which players update their beliefs about rivals while using a noisy best response.

[5] Crawford (2002) argues that by foregoing repetition as a teaching device, one-shot experiments place a heavier burden on subjects' understanding, with a premium on simplicity and clarity of design.

[6] See Austin and Delaney (1998), Crutcher (1994) and Ericsson and Simon (1993).

[7] There exists however an increasing tendency in Economics to use subjects' self-reports to explain laboratory choices and go beyond using this information as just anecdotal evidence. A successful example is Apesteguia et al. (2007).

situations such as the TD contain informational value which can be useful to predict behavior in other simple related tasks and strategic situations.

Basu et al. (forthcoming) also used subjects' self reports in a traveler's dilemma experiment. They find a set of reported strategies which up to some point nicely correspond to our principal components, although the relative weight of each of the alleged reasons differs and they do not group statements in principal components. The research objective of their paper differs from ours, since Basu et al.'s (forthcoming) main interest are the reasons behind choices in the TD and they focus on how changes in the sizes of each subject's penalty influence choices in the TD. Our paper aims at identifying types of players and on studying whether self-reports help predicting behavior in other tasks and experiments.

The paper is organized as follows. Section 2 introduces the experimental design and describes subjects' choices in the TD. Section 3 explains how principal components (PCs) were extracted from subjects' self-reported comments. Section 4 shows how PCs explain subjects' choices in the TD. Section 5 studies the relationship between PCs and subjects' choices in other tasks and experiments. Section 6 concludes. Appendices available online include additional calculations (Appendix A), instructions for the TD experiment (Appendix B), instructions given to data codifiers (Appendix C) and descriptive statistics not included in the paper (Appendix D).

2. Experimental design, procedures and results

The complete set of experimental data reported in this paper was collected during the spring semester 2005 in several sessions with first year Economics students at Universidad de Granada (Spain). Subjects were informed that the number of experimental points obtained during each of the sessions in which they would participate contributed to their final grade in their Microeconomics I course in the following way. Subjects belonged to four different sections of around sixty subjects each. The total number of experimental points obtained by a subject during the course was added to determine his/her position within his/her section's ranking. The subject with the highest number of experimental points added three extra grade points (out of a maximum of ten) to his/her final grade. For each position below, grade points were calculated as a function of the distance from the winner:

$$Grade \quad points = 3 - 0.05d,$$

where d is the distance from the winner. For example, a subject in the tenth position in a a section is at $d=9$ and therefore earned *Grade points* $= 3 - (0.05x \times 9) = 2.55$ grade points. Subjects were not informed of their performance and others' performances in any of the experiments and tasks until all experiments had concluded.[8]

The sequence of experiments carried out by subjects was as follows: a dictator game (March), a GRE-type math test (beginning of April), risk aversion experiments (end of April), and the session detailed below containing four tasks (June). Data from all sessions were gathered and added to an ongoing database at Universidad de Granada which contains information about subjects' behavior across experiments and their academic performance.

The final experimental sessions referred above (June) contained the traveler's dilemma experiment and are thus the main focus of this paper. In these sessions subjects performed four tasks: (i) predict their relative performance in the final Microeconomics I exam with respect to other students in their class; (ii) decide between a binary lottery and the outcome of a 2×2 game in which they played; (iii) choose a number in a TD and give an explanation for their decision and (iv) predict their overall performance in the courses taken during that term.

Experimental procedures for these final sessions were as follows: Once in the classroom and during the usual time slot for Microeconomics I, students were handed instructions for the four tasks. They were asked to perform the tasks in no particular order. With respect to the TD, they were informed that they had been randomly matched with another student from the same group. They were handed instructions and asked to choose a number in the interval [20,120], to which we will refer as their choice (b). They were also asked to voluntarily provide written comments – on the same answer sheet – on how they had reached their decision. After one hour, students handed back the answer sheets for all four tasks and left. Students were informed about their performance in all experimental sessions at the end of the course and graded accordingly, once all experiments had finished.

The TD was framed as two firms competing in prices, such that the content of the experiment could be used to explain oligopolistic competition in subsequent Microeconomics courses.[9] Notice that at the time of the experiment, subjects had received no lectures on oligopolistic competition nor on Game Theory. It is true that the frame of firms fixing prices may have not only affected subjects' choices but also their reasoning process, and thus the reasons behind our results may not perfectly apply to other experiments with the TD in which no frame or a different frame is used. In any case, results below

[8] Grade rewards were used in all experiments carried out with these subjects. Administrative and financial constraints prevented us from using monetary incentives. Rubinstein (2007) reports a similar percentage of non-equilibrium choices to previous TD experiments with monetary incentives in a TD experiment with no rewards.

[9] The game is similar to a Bertrand duopoly in which firms have to choose prices from a given set. The analogy is not perfect since in our game, the firm choosing the lowest price does not sell to the whole market. However, it is sufficiently close to a duopoly model in which there is some product differentiation. In any case, few subjects mentioned the market framing and subjects' explanations indicate that they understood the strategic situation they were facing.

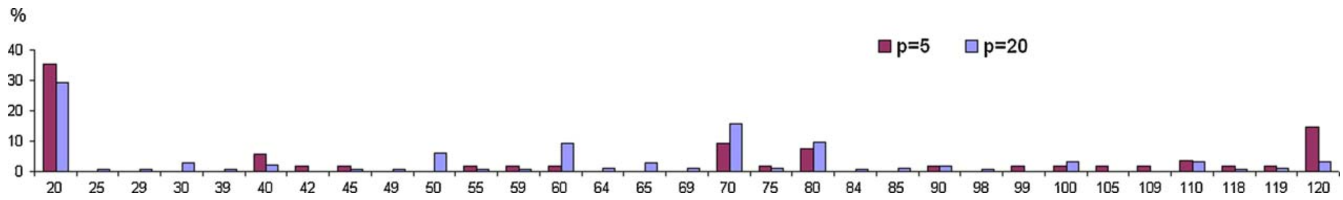

Fig. 1. Choices and penalty size in the Traveler's dilemma ($n = 238$).

show that the distribution of heterogeneous choices was clearly similar to the usually obtained results in TD experiments with neutral frame.

There were 243 subjects participating in the experimental sessions containing the TD; 241 turned in an answer for the TD game, although three subjects answered with an interval instead of a number so that these three observations were eliminated, leaving 238 valid observations of the TD.

There were two treatments varying in the size of the penalty p in the TD. Students in three groups (184 subjects) were assigned to the treatment with penalty size $p = 20$, while students in the fourth group (54 subjects) faced a penalty $p = 5$.[10] Fig. 1 shows the distribution of subjects' choices in the TD for the two penalty sizes.

Although a significant percentage of subjects made Nash Equilibrium choices ($b = 20$), a higher proportion of subjects in both treatments made different choices (65% with $p = 5$, 71% with $p = 20$). The distribution of choices maintains the same properties as previous experimental tests of the TD.[11] First, there are choices all around the interval. Second, the distribution shows three peaks: (i) the Equilibrium prediction ($b = 20$), (ii) choices around the average of the interval ($b = 70$), and (iii) the highest possible number ($b = 120$). With respect to previous research, our distribution shows a slightly higher percentage of equilibrium choices [12] A Mann–Whitney test comparing the distributions under both penalty sizes shows that they are not statistically different ($z = -0.968$, p-value = 0.33) and thus we conclude that the size of the penalty made no difference.[13] Therefore, in the following we merge data with both penalty sizes.

In sum, as in previous experiments on the TD, we observe a high percentage of non-equilibrium heterogeneous choices. In the following section we turn to subjects' own explanations of their behavior to study whether there were also heterogeneous reasons driving these choices.

3. Principal components analysis

3.1. Codification of subjects' comments into variables

Our aim was to use an independent, systematic and judgement-free method to codify in a standard response format the comments voluntarily written by subjects after they had played the TD. We asked two independent research assistants to help us in this task.

First, we started by reading subjects' comments. We defined 26 ternary variables taking values {0,1,2} and referring to the content in subjects' comments and its sign. If a subject's comment did not contain any information on a particular variable, such variable would take value zero, while it would take value 1 if the comment contained it and its effect went in one direction and 2 if the comment contained it but its effect went in the opposite direction. For example, the variable *Risk* would take value 1 if the subject expressed that her decision was motivated to avoid risk, while it would take value 2 if it expressed that she was willing to take risks. The variable would take value 0 if risk was not mentioned.[14]

Second, our two independent research assistants (RAs) received instructions on how to codify subjects' comments into variables.[15] RAs were not informed of the objective of our study.[16] They were explicitly told that their task was to capture and classify what had been said rather than to interpret or rationalize subjects' choices.[17] Both RAs worked separately and independently and only met at the time of receiving instructions. There were no requirements on the number of variables used for each subject and RAs were allowed to create new variables if they thought

[10] Previous experiments with the TD show that the Nash equilibrium is a relatively better prediction with high incentives (high p). Our highest penalty ($p = 20$) provides relatively lower incentives than the highest penalty in previous experiments designed to study how behavior changes with the penalty size (Capra et al., 1999). We did so expecting to obtain more heterogenous choices in the TD.

[11] Capra et al. (1999), Goeree and Holt (2001), Cabrera et al. (2007), Becker et al. (2005), Rubinstein (2006, 2007), Basu et al. (forthcoming) and Becchetti et al. (2009).

[12] Suetens and Potters (2007) review the experimental evidence on Betrand duopoly and find that Bertrand produces more collusive behavior than Cournot.

[13] Capra et al. (1999) show changes in the distribution when varying the penalty size, but penalty changes were much more pronounced (from 5 units to 80 units, when choices could be made in the interval [80,200]). Rubinstein (2006) uses a single hypothetical $5 penalty when choices are made in a [180,300] interval.

[14] Variables *Calc* and *Error* were binary (0 or 1), as its content could not take different directions.

[15] The definition of variables and written instructions given to RAs can be found in Appendix C.

[16] The RAs hold a B.Sc. in Physics (coder 1) and a B.Sc. in Mathematics (coder 2). At the time, they were enrolled in a Ph.D. program in Quantitative Finance.

[17] Our methods closely followed the methodology in Brandts and Cooper (2007) and Cooper and Kagel (2005).

Table 1
Subjects explanations of own choices in the TD.

x	%	Content	*x*	%	Content
CONCERNS			STRATEGY		
*Risk*1	13.4^{+}	Risk averse	*Average*1	19.3^{+}	Average
*Risk*2	4.6	Risk loving	*Average*2	5.5^{+}	≠ Average
*Zero*1	32.8^{+}	Win zero averse	20_1	1.3	Focal Point 20
*Zero*2	0.4	Win zero like	120_1	5.0^{+}	Focal Point 120
*Win*1	9.7^{+}	Win loving	*Coord*1	1.7	Coordinate
*Win*2	1.3	Win aversion	*Cut*1	10.5^{+}	Undercut rival
*Penalty*1	6.3^{+}	Penalty averse	*CutC*1	5.0^{+}	Undercut 1 unit
*Size*1	0.4	Penalty high	*CutC*2	3.4	Undercut >1 unit
*Size*1	0.8	Penalty low	*CutR*1	0.8	Undercut twice
*Lose*1	7.6^{+}	Loss aversion	*Low*1	17.6^{+}	Choice is low
*Aspi*1	7.6^{+}	Aspiration low	*Low*1	5.0^{+}	Choice is high
*Aspi*2	5.0^{+}	Aspiration high	RIVALS		
			*Prob*1	28.6^{+}	Probability beliefs
REASONING			*Prob*1	0.4	Point beliefs
*Calc*1	20.2^{+}	Calculations	*High*1	14.7^{+}	Beliefs high
*Theory*1	8.4^{+}	Economic theory	*Higher*1	13.9^{+}	Beliefs higher
*Error*1	8.8^{+}	Errors	*Higher*2	0.4	Beliefs lower
*Nolog*2	0.8	Solvable	*AverageR*1	2.9	Beliefs average
*Nolog*1	6.3^{+}	Unsolvable	*AverageR*1	0.4	Beliefs not average
*Ermean*2	10.1^{+}	Average is 70			
*Ermean*1	4.2	Average not 70	INTERDEPENDENT PREFERENCES		
			*Soci*1	3.4	Equity
			*Fair*1	0.4	Fairness
			*Soci*2	12.2^{+}	Competitive

they were necessary, although they did not do so. RAs returned two spreadsheets associating subjects' comments to variables.

No effort was made to force agreement between coders. One of the coders was more prone to classify comments into variables than the other. While coder 1 gave a positive value to 843 entries (13.62% out of $238 \times 26 = 6188$ entries), coder 2 gave a positive value to 525 entries (8.48%). In any case, the degree of agreement between both coders was relatively high. Taking the average over the value of all original ternary variables for all subjects, both coders assigned the same value (0, 1 or 2) to 92.26% of them.[18] Coders never disagreed on the direction of the original ternary variables.

Once this information was collected, we duplicated the number of variables by transforming the ternary variables (0, 1 or 2) into dummy variables (0 or 1) reflecting the direction of the comment that the variable captures. For example, the variable *Risk*, became two variables: *Risk*1 (1 if wanting to avoid risk, 0 if it did not refer to risk) and *Risk*2 (1 if wanting to take risks, 0 if it did not refer to risk).[19]

Our analysis below shows that this codification of subjects' self-reports proved useful in explaining subjects' choices in the TD.

3.2. Descriptive statistics of subjects' comments

Table 1 shows the percentage of subjects whose comments were reflected in our dummy variables (x) at least according to one of the coders. The table contains a brief description of the meaning of the variables. Variables are classified in five groups. The names used to describe these groups are only orientative and should help the reader, but they were never used in the analysis.

- CONCERNS includes variables referring to subjects' motivations for their choices: attitudes towards risk, loss aversion, aspiration levels, etc.
- REASONING refers to subjects' procedures to reach their decision: whether they wrote calculations on their answer sheets, used economic theories to help them make a decision, understood the game or thought they could reach a solution through logical reasoning.
- STRATEGY refers to own decisions: choosing the middle of the interval or one of the extremes, undercutting the predicted rival's choices, or choosing (or not) a high value.
- RIVALS refers to beliefs about rivals' choices: whether they mentioned a possible distribution for rivals' choices or had point beliefs, thought their rival would choose a high value, a higher value than their own, etc.

[18] Maximum agreement was reached in variables *CutR* and *Fair* (100%) while minimum agreement occurred in variable *Zero* (70.17%).
[19] Definitions for the ternary variables appear in the Instructions for coders in Appendix C, and from them it is immediate to obtain the dummy variables.

- INTERDEPENDENT PREFERENCES includes variables reflecting equity considerations, appreciation for fairness or desire to compete.

Variables which both coders thought were absent were eliminated.[20] Notice that no subject mentioned choosing a number due to it being "an equilibrium" neither explicit equilibrium reasoning was found in subjects' comments. No individual mentioned imitating their rival. In contrast, some of them tried to coordinate typically on 120.

There exists notable heterogeneity on the explanations given by subjects for their choices in the TD. Some reasons were mentioned by a low percentage of subjects. We eliminated from the following analysis those variables mentioned by less than 5% of the subjects. This leaves us with the 23 variables that appear with a $^{+}$ sign in Table 1.[21]

As it is frequently argued in protocol analysis, our variables may just be a subset of the reasons that could have influenced subjects' choices. In any case, there are a number of arguments which were prominent and systematically repeated in subjects' comments. Subjects' main concerns were risk and earning no payoff (*Risk*1, *Zero*1) and they also expressed a desire to "win" (*Win*1). A significant proportion of subjects used mathematical calculations to come up with a choice (*Calc*1) and some of them mentioned the average of the interval (*Ermean*2). Among the most quoted strategies were either choosing low or intermediate values and undercutting rivals' choices (*Low*1, *Average*1 and *Cut*1, respectively). With respect to opponents, many subjects provided information about their subjective probability distribution on rivals' choices (*Prob*1), and/or stated beliefs indicating that rivals may choose high values or higher values than their own (*High*1 and *Higher*1). Finally, subjects indicated a preference for earning more than their rivals (*Soci*2). Notice that more altruistic forms of social preferences such as fairness or equity concerns (*Fair*1, *Soci*1) were barely mentioned.[22]

3.3. Converting variables into indexes

To convert the above information into a more tractable data set, for each variable x we created an *index* variable adding up the value of the dummies assigned by each of the two coders ($d_1(x)$ and $d_2(x)$).

$$index(x) = d_1(x) + d_2(x).$$

Our *index* variables take value 0 if no coder thought the subject's comment referred to such variable, value 1 if one of the coders thought it did and value 2 if both coders thought the variable was mentioned. Given the lack of complete agreement among coders, our index may be interpreted as reflecting the degree of intensity in the codification of each variable. Out of a possible total of 5474 entries (238 subjects $\times$ 23 dummy variables), there were 4823 zeros (88.1%), 435 one's (7.9%) and 216 two's (3.9%). An alternative would have been to have let data decide which of the two coders was more effective and use only such coder's classification. However, we favour having independent classifications and a measure of intensity.

Next we explain how we turned the index variables into principal components (PC).

3.4. Principal components analysis

Given the nature and length of our data set, the use of PC analysis was natural: (i) we were interested in summarizing the information obtained through codification in a more tractable format; and (ii) several variables may have conveyed the same information. For example, we were uncertain a priory about the possible relationship between *loss* and *risk aversion*.

The most salient features of PC analysis are precisely that (1) it *reduces* the number of variables and (2) it *detects structure* in the relationships between them, i.e., it *classifies variable*s according to their content. We extracted 6 principal components explaining 48.5% of the variance.[23] Appendix A (available online) shows the matrix of rotated components with their saturation level.

Table 2 shows the indexes associated to each of the PCs and their saturation level. We identified which indexes are predominant in each new PC through their saturation level. Our selection criteria were to assign each original index to the component in which it shows its highest value as long as this value is clearly highest for one PC.[24] We assign an orientative name to each of the PCs (Name) and we briefly remind the content of the indexes that form each PC (Explanation). The last column shows the scoring of each index in its component and the direction of its participation (its sign).

[20] This was the case for variables *Penalty*2, *Lose*2, *Cut*2, *CutR*2, *Fair*2, 20_2, 120_2, and *Coord*2. *Theory2* was eliminated for being redundant.

[21] Qualitative results form the remaining of the paper were maintained when all variables were included in the analysis.

[22] This may be partially induced by using grade points as rewards which depend on the overall relative performance across all experiments and tasks.

[23] We did not predefine the number of orthogonal components, rather we used as extraction criterion an eigenvalue higher than 1 ($\lambda \geq 1$); we also did not limit the number of computational iterations. To study the significance of each component, we rotated the new variable using the Varimax–Kaiser procedure. Initially we got nine components including three with only one variable which did not contribute much in terms of interpretation or explained variance.

[24] Indexes *Zero1*, *Theory1* and *Nolog1*, disappear of the analysis as they score low and similar values in more than one PC.

Table 2
Indexes associated to principal components.

PC	Name	Index	Explanation	Saturation
PC1	*Undercutting*	*Cut*1	Undercuts on rival	0.825
		*CutC*1	Undercuts 1 unit	0.709
		*Higher*1	Rival chooses higher	0.673
		*Prob*1	Uses probability	0.619
		120_1	Rival chooses 120	0.562
		*High*1	Rival chooses high	0.560
PC2	*Aspirations*	*Low*2	Considers own choice as high	0.800
		*Aspi*2	Aspires to high value	0.692
PC3	*Competitive*	*Soci*2	Wants to earn more than rival	0.801
		*Win*1	Wants to beat rival	0.760
PC4	*Risk aversion*	*Aspi*1	Expects low value	0.663
		*Risk*1	Risk averse	0.634
		*Low*1	Choice is low	0.503
		*Lose*1	Hates to earn less than rival	0.395
PC5	*Average*	*Ermean*2	Mean is 70	0.637
		*Average*2	Chooses not mean	0.582
		*Average*1	Chooses the mean	0.444
PC6	*Penalty*	*Penalty*1	Penalty averse	0.454
		*Calc*1	Writes calculations	−0.477
		*Error*1	Errors calculating payoffs	−0.653

The indexes grouped under each PC and presented in Table 2 suggest consistent arguments for making a choice and it is straightforward to derive a behavioral prediction from subjects classified under each PC, as we later do in Table 4.[25]

The set of indexes contained in **PC1** indicates that there is a number of subjects who reason in terms of probability distributions on choices (*Prob*1) and believe that this distribution has more weight on high values (*High*1, *Higher*1, 120_1). Given these beliefs subjects show some level of iterative reasoning as they best respond by *Undercutting* the choice they expect from their rivals (*Cut*1, *CutC*1).[26] Accordingly choices made by subjects scoring high in this component should be made in the high part of the interval, but should be lower than the highest value (<120), as subjects undercut on their rival. Depending on the exact expectation subjects may have on their rivals' choice, their choice may be spread along the interval. Undercutting behavior may thus contribute to the dispersion of choices. The second component, **PC2**, includes indexes reflecting high payoff aspirations (*Aspi*2) and, consequently high choices (*Low*2). We thus label PC2 as *Aspirations*. Subjects scoring high in PC2 should made choices in the high part of the interval. **PC3** reflects *Competitive* behavior. In particular, indexes scoring high in this PC correspond to motivations such as earning more than rivals (*Soci*2), or desire to beat them (*Win*1). The indexes contained in PC3 suggest that subjects should choose the lowest possible number (20) in order to beat their rival and prevent him/her from earning more than them. **PC4** refers to choices partly motivated by *Risk aversion*. Indexes scoring high in this PC reflect desire to avoid risks (*Risk*1, *Lose*1) and thus, acknowledgement of low values chosen (*Low*1) and low aspiration values (*Aspi*1). Since subjects scoring high in PC4 indicate their desire to avoid risk and losses and acknowledge and expect to obtain low numbers, they should choose the lowest possible number (20). **PC5** contains indexes related to comments made about the *Average* of the interval. For example, stating its value (*Ermean*2) or justifying choices due to precisely being in the average of the interval (*Average*1) or close to it, but not being the average (*Average*2). Therefore, we should expect choices from subjects scoring high in PC5 to be in the middle of the interval (around 70). Finally, **PC6** includes two types of variables: subjects who are averse to being penalized (*Penalty*1) and subjects who make calculations (*Calc*1) or make mistakes in calculating payoffs (*Error*1). There exist no clear a priory relationship among the indexes grouped in PC6.Therefore, the prediction of choices made by subjects scoring high in PC6 is not so clear cut. Aversion to being penalized should drive subjects to make low choices, but other indexes in PC6 do not allow to make clear predictions. As such, we expect these choices to be spread along the interval.

There are two important remarks concerning the interpretation of principal components:

(i) We interpret the components as types of behavior, in the sense that they represent the revealed motivations driving subjects' choices.
(ii) Principal components and thus types, are uncorrelated. Although any subject might exhibit a combination of these types, there exists no systematic relationship among them.

[25] Using a different number of PCs does not yield a different result. For example, with 9 PCs the first four are identical and the fifth and sixth are very similar.

[26] Notice that subjects scoring high in PC1 justify their choices following a similar reasoning to the *L1* cognitive level as defined by Stahl and Wilson (1994, 1995). Few subjects justified their choices using higher levels of iterative reasoning such as *L2*, since variables like *Cut2, CutC2* and *CutR2* were rarely codified.

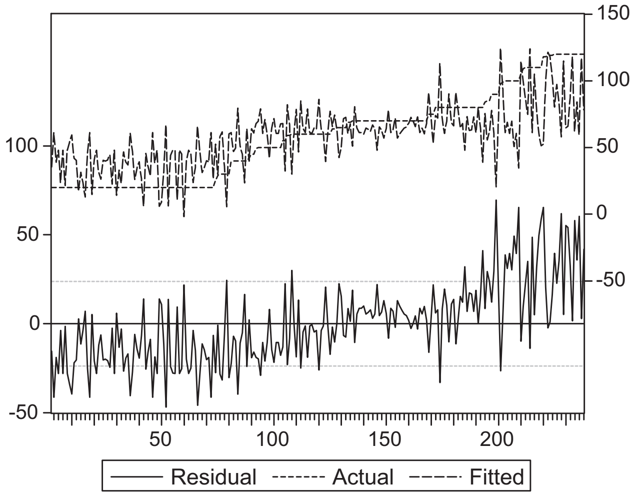

Fig. 2. Actual vs. fitted choices.

Regarding choice predictions, Fig. 2 shows that choice predictions for subjects scoring high in each component were relatively well fulfilled. Notice that PC3 and PC4 predict the same choice as the unique Nash equilibrium of the TD. Although people using equilibrium reasoning may be motivated by some of the variables contained in this PCs, notice that no subject justified their choice with equilibrium arguments.

In the next section we check whether the different types help us in predicting choices in the TD.

4. Predicting TD choices through principal components

We now check coherence between subjects' comments, summarized in the PCs, and their choices. Given the indexes contained in each of the PCs we conjecture that: (i) PC1 (*Undercutting*) and PC2 (*Aspirations*) have a positive impact on choices. (ii) PC3 (*Competitive*), PC4 (*Risk Aversion*) and PC6 (*Penalty*) have a negative impact. (iii) PC5 (*Average*) drives choices towards the average of the interval.

Table 3 shows the result of Tobit censored regression and a simultaneous quantile regression (SQR) of each subject's choice in the TD with the 6 principal components as regressors. In our TD, the position of the choice along the distribution is not trivial. Therefore, a proper analysis by quantiles seems to be appropriate. The SQR technique estimates a regression for each quantile and produces a vector of corrected errors (VCE) via bootstrapping, where the VCE includes between-quantile blocks. The interpretation of the coefficients of the QSR in Table 3 is as in any regression model. The comparison between both estimations (tobit and SQR) shows coefficients of the same sign and order of magnitude, which allows us to conclude that the information of the distribution does not have important effects. Notice that all PCs are significant (p-values of virtually 0 and have the expected sign), apart from the coefficient of PC5 which equals 0.077.

Fig. 2 shows the differences between actual and fitted choices. Interestingly, low and intermediate values are better fitted than high ones, which are underestimated.

We now identify different *types* of subjects following their self-reported main motivation for their choices in the TD. For each subject, we counted the number of indexes showing a positive value in each PC. We then assign each subject to the PC in which she scores highest. For example, according to our RAs, subject 3 scored a positive value in 4 of the indexes contained in PC1 and 1 of the indexes in PC5. We thus classify subject 3 as PC1. Although there are several ties, we are able to classify 144 subjects (60.5% of the subject pool) using this simple method. We focus only on these cases. Table 4 reports the percentage of the 144 subjects classified in each PC along with their average choice in the TD and standard deviations. Very few of these 144 subjects were classified as PC2 and PC3. Notice that subjects classified in each PC make on average choices which are consistent with the interpretation previously given to each PC. High choices are taken on average by subjects classified as PC1 and PC2, which constitute around one third of the subject pool. Choices around the mean of the interval are

Table 3
PCs driving TD choices (tobit regression) ($n = 238$).

PC	Name	b (Tobit)	b (QSR)
Constant		50.21	56.71
PC1	*Undercutting*	12.47	12.16
PC1	*Aspiration*	15.09	11.51
PC3	*Competitive*	−12.47	−8.35
PC4	*Risk aversion*	−18.76	−12.87
PC5	*Average*	7.61	3.28
PC6	*Penalty*	−15.03	−9.09

Table 4
Subjects classified by PCs ($n = 144$).

Subject type	Explanation	% of subjects	Average choice	Standard deviation
PC1	*Undercutting*	29.17	83.48	29.54
PC2	*Aspirations*	2.08	100	20
PC3	*Competitive*	6.25	37	34.19
PC4	*Loss aversion*	20.83	28.33	17.77
PC5	*Average*	23.61	67.46	9.76
PC6	*Penalty*	18.06	39.55	31.49

taken on average by subjects classified as PC5, which are almost one fourth of the subjects. Finally, low choices are made, as expected, by those subjects classified as PC3, PC4, and PC6.

Overall, we have been able to identify different types of subjects whose heterogeneous choices in the TD are justified by heterogeneous reasons. Subjects self-reporting similar reasons make similar choices which coincide with our initial conjectures. The most important reasons driving choices in the TD are related to strategic and iterative reasoning (PC1), high payoff aspirations (PC2), competitive preferences (PC3), attitudes towards risk and losses (PC4) and focal points such as the average of the interval (PC5).[27] In the following section we check whether these identified types are consistent with some of subjects' personal characteristics and their choices in independent tasks and experiments.

5. Type coherence across tasks

The following variables were obtained from the same sample of subjects performing different tasks in the experimental sessions detailed in Section 2. The number of observations (n) was not the same across tasks, as some individuals were absent from certain experimental sessions and some answers were erroneously reported in the session containing the TD (June session).

We first describe the variables related to subjects' personal characteristics or attitudes:

Gender: A dummy variable (1 = male, 2 = female).
GRE: Subjects' scores in a GRE-type math test containing 25 mathematics questions.
Self-evaluation: Proportion of correct answers subjects expected to get in the GRE-type test.
Optimism: Average grade subjects expected to obtain in the second term exams minus average grade obtained in the first term.

We now describe those variables which reflect subjects' choices in other experiments:

Selfish: A dummy variable indicating how much subjects gave compared to the median of the subjects in their treatment playing the same dictator game (1 = gave less, 0 = gave equal or more).[28]
Risk-love: A variable in the interval [0,10] indicating how much a subject has to be paid to avoid playing a 2×2 game with uncertain outcome. This variable may reflect the degree of individuals' strategic risk-love.
Lottery-aversion: A variable in the interval [0,1] which reflects the average degree of risk-aversion showed by individuals playing four different lotteries.[29]

First we explore the correlations among the variables regarding personal characteristics together with the principal components. Table 5 reports Pearson-χ^2 tests among both types of variables. The number in parenthesis indicates p-values while the number on brackets shows the number of observations available for each of the personal characteristics. Numbers in bold indicate significant coefficients at the 10% level or better. The last line in the table shows correlations between choices in the TD and personal characteristics.

Our *GRE* variable measures mathematical skills, which may be related to subjects' analytical and cognitive abilities, and thus we may expect that subjects using more cognitively demanding justifications for their TD choices may be those who score high in the GRE-type math test.[30] Table 5 indicates that individuals' math abilities are positively correlated to *PC*1.

Self-evaluation may capture how confident subjects feel about their abilities. Confident subjects may thus expect to obtain high payoffs, and in particular they may aspire to a high payoff in the TD. Therefore the positive relationship observed between *self-evaluation* and *PC*2 (*Aspirations*) was to be expected. Additionally, the negative correlation between *self-evaluation* and *PC*4 may indicate that confident subjects are not concerned about the strategic uncertainty in the TD, as they may feel assured they will obtain high payoffs.

27 As previously mentioned, PC6, which captures the lowest percentage of the variance, has a less clear interpretation.
28 We created this variable because different groups played dictator games with different initial allocations.
29 As described in Brañas-Garza et al. (2008).
30 Notice that undercutting rivals' choices is a cognitively demanding reasoning process according to the literature on K-level thinking (starting with Stahl and Wilson, 1994).

Table 5
Personal characteristics (χ^2 correlations).

	GRE	Self-evaluation	Optimism	Gender
*PC*1	**0.21** (0.00)	0.05 (0.38)	0.11 (0.14)	−**0.19** (0.00)
Undercutting	[180]	[224]	[176]	[238]
*PC*2	0.07 (0.30)	**0.12** (0.06)	**0.12** (0.10)	−**0.11** (0.08)
Aspirations	[180]	[224]	[176]	[238]
*PC*3	0.10 (0.17)	0.07 (0.25)	−0.02 (0.79)	−0.04 (0.50)
Competitive	[180]	[224]	[176]	[238]
*PC*4	−0.10 (0.16)	−**0.11** (0.09)	0.03 (0.65)	**0.10** (0.10)
Risk aversion	[180]	[224]	[176]	[238]
*PC*5	−0.05 (0.47)	0.04 (0.55)	0.05 (0.44)	**0.18** (0.00)
Average	[180]	[224]	[176]	[238]
*PC*6	0.01 (0.88)	−0.02 (0.68)	−0.00 (0.92)	−0.04 (0.52)
Penalty	[180]	[224]	[176]	[238]
TD choice	0.10 (0.17)	**0.11** (0.09)	**0.12** (0.10)	−**0.10** (0.10)
	[180]	[224]	[176]	[238]

(*p*-value) and [sample size]. Numbers in bold indicate statistical significance.

Optimism may relate to the expectation of getting better outcomes than previously obtained. This optimism may drive subjects to hold high aspirations in the TD, which would explain the positive correlation between *optimism* and *PC*4.

We also observe some *Gender* effects. In the TD, *men* are more likely to *undercut* their rivals (*PC*1) and have higher *aspirations* (*PC*2). On the contrary, women express more concerns about *risk* (*PC*4) and tend to mention choosing values because of their proximity to the *average* of the interval (*PC*5).

Finally, we find that the analysis nicely extends to the correlation between personal characteristics and choices in the TD. We find that *Self-evaluation* and *Optimism* are positively correlated (at the 10% level) with choices in the TD, which may be explained by self-confident and optimistic subjects expecting to obtain higher payoffs in the TD and thus making high choices. With respect to gender effects, we find negative correlation between *Gender* and choices in the TD, which, as we explained below, may be due to higher risk aversion among women.

Now we check the possible relationship between choices in different experiments. The heterogeneity observed in the different justifications of subjects' actions in the TD, makes it an ideal candidate to study the translation of subjects' motivations across tasks. In such case, we would expect PCs to be able to capture subjects' intrinsic motivations not only in TD but in other experimental tasks, and thus there may exist an intrinsic component in defining *types of subjects*, which may not be completely task-dependent. For example, we want to check whether those individuals mentioning risk concerns in the TD are those behaving as risk averse when facing lotteries. Table 6 reports regressions of dictator game choices (*selfishness*), choices under uncertainty involving strategic risk (*risk-loving*), and lottery choices (*lottery-aversion*) on the six PCs obtained from the TD. Therefore, we should observe significant coefficients for those PCs capturing the most relevant feature for each task.

Notice that the translation of the motivations captured by PCs to other tasks may not be perfect. For example, subjects in the TD may have mentioned only a subset of the motivations driving their choices. However, we should expect that self-reports may reveal the most prominent motivation underlying TD choices, and thus, our exercise may show meaningful results. Table 6 shows that most of the significant coefficients in our regressions have the expected sign and are easy to interpret. Below we discuss the significant coefficients for each of the PCs.

The most salient results appear in bold in Table 6. We now describe a possible interpretation of the results:

First, subjects reporting their choices were motivated by a desire to avoid risks (*PC*4) are precisely those who also avoided strategic risk (*risk-love*). Consistently, they are also those who are more risk averse (*lottery-aversion*).

Second, subjects justifying their TD choices using arguments contained in *PC*1 (*Undercutting*) less prone to buy *insurance* in lotteries (*lottery-aversion*), which may be related to the fact that those who choose high values in the TD may underestimate the risk of obtaining bad outcomes. This same behavior would lead them to buy less insurance in other uncertain situations such as lotteries.

Table 6
Predicting actions (probit and tobit regressions).

		Selfishness Probit	*Risk-love* Tobit	*Lottery-aversion* Tobit
*PC*1	*Undercutting*	−0.29 (0.75)	0.05 (0.58)	−**0.04** (0.00)
*PC*2	*Aspirations*	**0.25** (0.01)	−0.78 (0.46)	**0.03** (0.02)
*PC*3	*Competitive*	0.07 (0.43)	0.08 (0.46)	−0.00 (0.60)
*PC*4	*Risk aversion*	−0.03 (0.71)	−**0.23** (0.02)	**0.03** (0.02)
*PC*5	*Average*	−0.07 (0.46)	0.03 (0.77)	0.00 (0.70)
*PC*6	*Penalty*	0.04 (0.69)	0.09 (0.40)	−0.00 (0.84)
Constant		−0.44 (0.00)	5.40 (0.00)	0.48 (0.00)
n		169	234	184

(*p*-value).

Finally, Subjects mentioning arguments contained in *PC*2 (*Aspirations*) aims to obtain a high payoff in the TD. This same behavior would lead them to keep everything for themselves in dictator games (*selfishness).* Such subjects are also more prone to buy insurance (*lottery-aversion*), possibly also in order to maintain their payoffs.

We finally performed regressions of the dictator game choice (*selfishness*), the choice under uncertainty involving strategic risk (*risk-loving*), and the lottery choices (*lottery-aversion*) on the choice in the TD. Although coefficients have the expected signs (positive for *selfishness* and *risk-loving*, negative for *lottery-aversion*), they are not statistically significant at standard levels. Although this result may seem disappointing at first, notice that if in this paper we have focused on self-reports, grouped under PCs, it is precisely because they indicate a unique driving motivation behind choices in the TD. On the other had, the same choice in the TD may be driven by several motivations which may not be reflected in the simples tasks and experiments we are correlating them with (dictator game, strategic risk and lotteries). Therefore, we should not expect that behavior would translate across tasks as well as motivations do.

6. Discussion

This paper starts by providing reasons behind observed heterogeneous behavior in a particular version of a one-shot traveler's dilemma experiment.

Our experiments were part of a larger tournament competition among students used to motivate learning during a Microeconomics course. Thus, we used a particular relative performance incentive structure and a particular frame (firms fixing prices). Our version of the TD maintains the same theoretical properties and a similar empirical distribution of heterogeneous choices as more standard versions of the TD. We use subjects' self-reported justifications for their behavior and we find that their claims turn out to be coherent and consistent reasons for making different choices in the TD. Among the most prominent arguments, we find that different levels of strategic sophistication, heterogeneous beliefs on opponents' choices, payoffs aspirations, competitive preferences, different degrees of risk and loss aversion and focal points such as the average of the interval are behind one-shot choices in our TD.

Although self-reported explanations are obtained using no incentives and they may only be a subset of the possible reasons leading to heterogeneous choices in the TD, we find that they are useful in understanding behavior. Thus, our paper is in line with recent experiments using a variety of sources easily available in the laboratory to obtain higher explanatory power than relying only in choices made in the laboratory. Similar recent approaches have successfully studied subjects' sequence of payoff look-ups to identify reasoning processes (Costa-Gomes and Crawford, 2006), elicited beliefs of opponents' choices (see Costa-Gomes and Weizsäcker, 2008), recorded communication among subjects (Brandts and Cooper, 2007) or measure response-times (see Rubinstein, 2007) to explain laboratory behavior.

The traveler's dilemma is an ideal game to study heterogeneous motivations behind behavior since the typical distribution of choices is heterogeneous. However, if we want to study how consistent those motivations are across different tasks, using only the actions observed in a TD experiment might not be enough. The reason is that we show that several different reasons may be behind the same TD choice. For example, we find several subjects choosing the equilibrium strategy but none of them claim to be using equilibrium reasoning. Thus, using self-reported justifications we are not only able to better understand choices in the TD, but also to identify types of motivations behind such choices.

Our main contribution consists in showing that some of such motivations are intrinsic to subjects. Thus we observe that motivations are coherent with choices by the same subjects in other tasks for which such motivations should be prominent. Although our results are limited to the number of tasks and experiments available using the same subjects, our paper is a first promising step towards identifying types of subjects in a given population. We have shown that it may be possible to predict subjects' behavior in different tasks using subjects' self-reported reasoning in other tasks. Further research aiming to identify the relationship between different types of individuals and their strategic behavior should follow.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.jebo.2010.12.005.

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