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Bounding preference parameters under different assumptions about beliefs: a partial identification approach

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Abstract We show how bounds around preferences parameters can be estimated under various levels of assumptions concerning the beliefs of senders in the investment game. We contrast these bounds with point estimates of the preference parameters obtained using non-incentivized subjective belief data. Our point estimates suggest that expected responses and social preferences both play a significant role in determining investment in the game. Moreover, these point estimates fall within our most reasonable bounds. This suggests that credible inferences can be obtained using non-incentivized beliefs.

Keywords Partial identification · Preferences · Beliefs · Decision making under uncertainty · Investment game

JEL Classification C81

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1 Introduction

A recent development in econometrics concerns the identification and estimation of econometric models that are partially identified (see Manski and Tamer 2002). A model is partially identified if it maintains weaker assumptions than necessary to point identify the parameters of interest. The approach allows researchers to understand what can be learned about a parameter of interest under different sets of assumptions, some potentially more plausible than others. Each set of assumptions can be used to place bounds around the model parameters of interest. These bounds in turn define the so-called identification region of the model parameters that contains all parameter vectors which are consistent with the data given the maintained assumptions. The identification regions can in turn be used to perform specification tests of the validity of maintaining stronger assumptions to point identify the model parameters. In particular, maintaining stronger but invalid assumptions concerning key variables may yield point estimates that fall outside the identification region derived under weaker assumptions.

Early applications have focused on placing bounds around moments or quantiles of a conditional distribution (see Manski 1989, 1994). These applications are nonparametric in nature: identification regions around moments or quantiles are estimated using the data alone without referring to a specific parametric model. More recently, the approach has been extended to make inferences on parameters of incomplete parametric and semi-parametric models (see Manski and Tamer 2002). Applications of the later include Honoré and Tamer (2006) and Ciliberto and Tamer (2009). To our knowledge, these methods have yet to be applied to experimental data.

In this paper we illustrate the usefulness of these methods by making inferences on preferences in a choice problem with uncertainty under different assumptions about the beliefs of players.[1] More specifically, we specify a simple model of sender behavior in a binary investment game (see Berg et al. 1995). We model decisions of senders as a function of their expected final payoffs (which proxies their trust in the responder), a component capturing other-regarding preferences, and an unobserved random component. We focus on relating the size of the identification regions to the restrictiveness of the assumptions maintained on the beliefs of senders. We explore three different sets of assumptions. The first and weakest set of assumptions states that researchers have no information about beliefs of senders apart from the natural restrictions imposed by the game (e.g., the amount returned must be below and above known boundaries). The second set of assumptions states that all senders expect to receive not less when they invest than when they do not. This second set is more restrictive than the first. As a result, we expect the identification region under the second set to be contained in the identification region derived under the first set of assumptions. The third and most restrictive set of assumptions we consider consists of assuming that senders have rational expectations. We show that the latter set of

[1] This paper relates to two approaches used so far to separately identify the effects of preferences and beliefs on decision making under uncertainty. The first approach compares behavior in treatments with uncertainty with behavior in treatments where uncertainty is blocked by design (see, e.g., Cox 2004). The second approach uses data on subjective beliefs to recover estimates of preference parameters (see, e.g., Bellemare et al. 2008).

assumptions produce the smallest identification region of the three we consider. Finally, we point estimate our model parameters using non-incentivized beliefs stated by senders in the experiment. Our point estimates suggests that expectations about responder behavior as well as other-regarding preferences are both significant determinants of investments. Moreover, we find that our point estimates fall within the first two identification regions. This suggests that reasonable inferences on preferences can be obtained using non-incentivized beliefs.

The rest of the paper is organized as follows. Section 2 presents the experimental design and the data. Section 3 the econometric model. Section 4 presents our results. Section 5 concludes.

2 Experimental design and procedure

2.1 Experimental design

Our experimental design is a modified version of the two player investment game of Berg et al. (1995). In our experiment, senders and responders were both endowed with 6$US.[2] Contrary to Berg et al. (1995), we restricted the decision space of senders to two choices: investing all or none of the endowment. If a sender invested his endowment, that amount was doubled and added to the endowment of the responder. In turn, the responder had the opportunity to return any amount from his augmented endowment to the sender (i.e., he could return up to 18$).[3] If the sender did not invest his endowment, the responder could return any amount from his initial endowment (up to 6$).

Responders made their decisions using the strategy method: they each had to decide how much to return when the sender invested his endowment, and how much to return when the sender would not invest his endowment. The decision that corresponded to the actual choice of the sender was chosen to be the effective action and determined the payoff of both participants. After making their decisions, senders were asked to state their subjective beliefs. Before stating their beliefs, they were further reminded of the decision tasks and given examples to clarify the belief elicitation procedure. Senders were not rewarded for the accuracy of their beliefs.

Senders had to state their subjective beliefs in two scenarios. They were first asked to state their beliefs if they did not invest. In particular, they had to state how many out of 100 responders would return 0$, and how many would return amounts in the following intervals $\{(0, 1], (1, 2], (2, 3], (3, 4], (4, 5], (5, 6]\}$.[4] By allowing senders to place a positive probability on getting back 0, we allow their subjective distribution functions to be censored from below. Additionally, senders were asked to state

[2]The complete content of the computer screens can be downloaded from http://www.ecn.ulaval.ca/charles.bellemare/.

[3]Expending the choice set of senders is in principle possible, but this will require asking each participant to answer many more questions on their beliefs (see below).

[4]If the probability mass entered exceeded 100, senders where automatically instructed to go back and adjust their answers.

their beliefs about responder behavior if they invested their endowment. Senders were asked to state how many out of 100 responders would return 0$, and how many would return amounts in the following intervals $\{(0,3], (3,6], (6,9], (9,12], (12,15], (15,18]\}$.[5,6]

2.2 Experimental procedure

After all participants had made their decisions, senders and responders were randomly matched and payoffs were computed based on the decisions of the pair. Participants were then informed of the outcome of the experiment and their final payoffs. The experiment was conducted in May 2005 at the Economic Science Laboratory at the University of Arizona using the software zTree (Fischbacher 2007). Participants were recruited via email and were mainly students in finance, business administration, economics, and engineering. Participants received a 5$ show-up fee upon arrival at the laboratory. We observed 38 pairs of players in 9 sessions of the experiment. An experimental session lasted on average 60 minutes, and, including their show up fee, participants earned on average 12.18$ (9.92$ for senders and 15.87$ for responders).

2.3 Descriptive statistics

24 of the 38 senders (63%) invested their endowment. To gain some insights on whether investors and non-investors trusted responders differently, we compare the subjective belief distributions of investors with those of non-investors. Figure 1 presents the average subjective belief distributions of investors (light bars, $N = 24$) and non investors (dark bars, $N = 14$). We find that both groups had similar beliefs about responder behavior if they consider not investing their endowment. In particular, both investors and non investors place on average a very high probability of getting nothing back from responders. In fact, we fail to find significant differences between the distribution of beliefs of investors and non-investors in each of the seven brackets of amounts reported in Fig. 1.[7]

Differences between both investors and non-investors emerge when we look at their beliefs when investing their endowment. There, non-investors placed a 48.3% probability on getting nothing back from responders, substantially less than the 24.6% probability placed by investors. A Mann-Whitney U test easily rejects the null

[5] In order to detect whether senders stated beliefs to rationalize their decisions, we randomized approximately one third of all participants in our experiment to a group of "observers" who did not make any decisions but who answered the belief questions after having read the same instructions as all other participants. Observers received each 6$ for their participation. We found no significant differences between the beliefs of senders and those of observers. See the extended working paper version of the paper for details (Bellemare et al. 2007).

[6] At the end of the experiment we elicited participants' risk preferences. We asked participants to play a sequence of lotteries similar to that proposed by Holt and Laury (2002). We will not discuss those results further as we found no significant relationship between measured risk preferences and investment behavior. Similar results have been reported by Eckel and Wilson (2004) and Houser et al. (2010).

[7] We tested for each interval $(0, (0, 1], \ldots)$ the null hypothesis the distributions of beliefs are the same for investors and non-investors using a Mann-Whitney U test. The lowest p-value out of the seven intervals tested is 0.238.

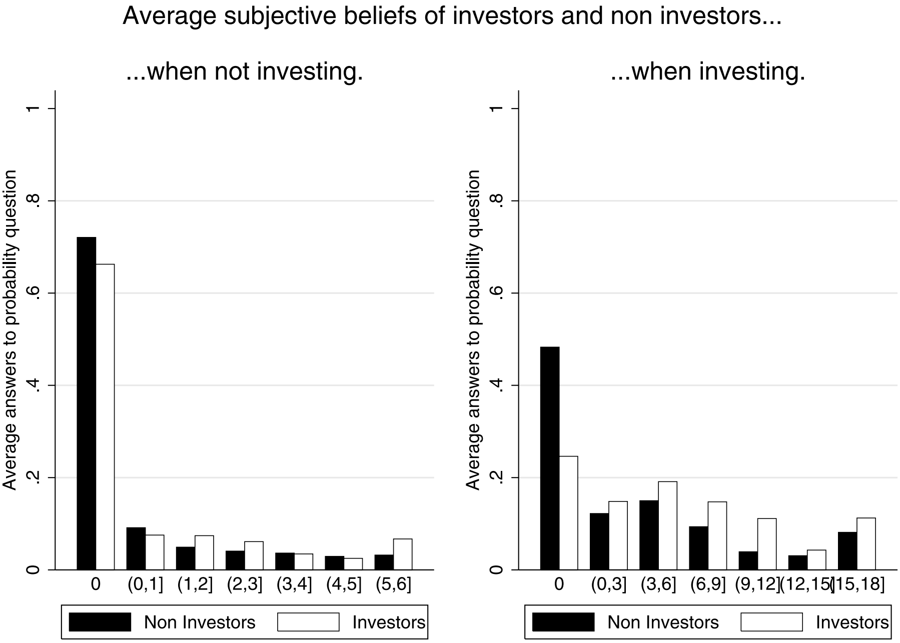


Fig. 1 Subjective beliefs about the amount returned separately for investors (*light bars*, $N = 24$) and non investors (*dark bars*, $N = 14$) when not investing (*left panel*) and when investing (*right panel*)

hypothesis that the distributions of beliefs about getting nothing back when investing are the same (p-value $= 0.012$). Moreover, Mann-Whitney U tests reject the null hypothesis that distributions of beliefs of investors and non-investors for the interval (9, 12] are the same (p-value $= 0.050$). Together these results suggest that investors expect to get more when investing their endowment than non-investors.[8]

To assess whether the beliefs of senders were rational, we computed for each sender the deviation of their subjective expectations about how much the responder would return when they would invest (when they would not invest) and the observed average amount returned for this case 0.26$ (observed average when not investing: 3.66$). Figure 2 presents the distributions of these differences. We find small discrepancies between expectations and observed responses when not investing, reflecting the fact that most senders correctly anticipated that the probability of getting close to nothing would be high when not investing. More substantial discrepancies emerge when considering amounts returned when investing. There, we find that a substantial amount of senders have expectations below and above the observed amount returned. Even though we fail to reject the Null hypothesis that the median deviation is equal to zero in both cases (p-value $= 0.545$ when not investing and 0.354 when investing), we find that the 25th and 75th percentiles of the distributions are signifi-

[8]We do not find significant differences between the distributions of beliefs of both groups in the intervals (0, 3], (3, 6], (6, 9], (12, 15], and (15, 18].

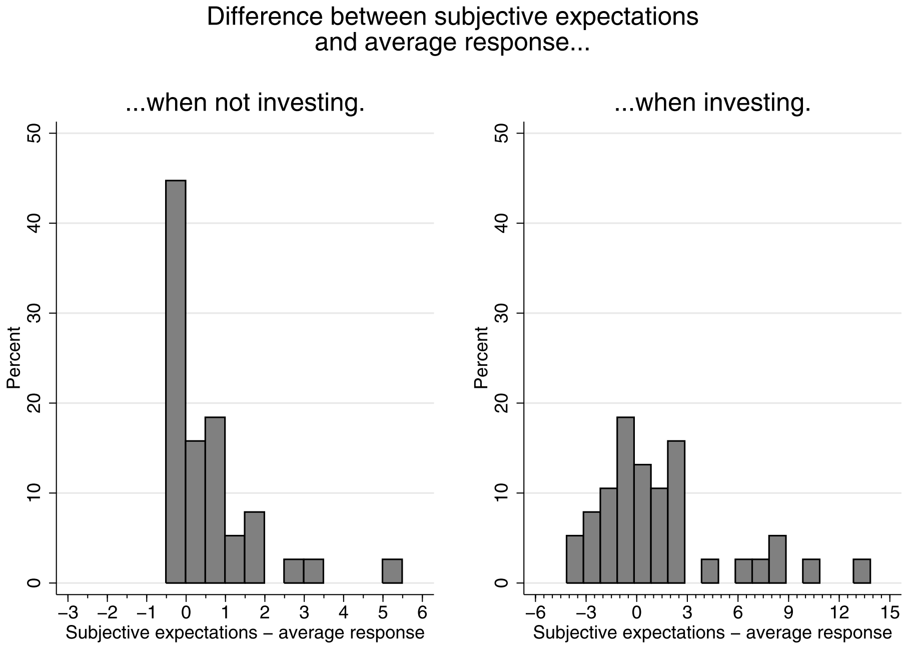


Fig. 2 Distribution of the difference between subjective expectations of all senders and observed average response of all responders in the event of not investing (*left graph*, $N = 38$) and in the event of investing (*right graph*, $N = 38$)

cantly different from 0.[9] Deviations observed in Fig. 2 may also reflect noise rather than genuine deviations from rational expectations. Separating noise from true underlying beliefs is out of the scope of the paper. However, if beliefs are mostly noise, they should be poorly related to decisions of senders. This issue is discussed in the next section.

3 A simple model of choice

We assume that the utility of not investing for sender i is given by $u_i^{keep} = \beta(w + r_i^{keep})$, where r_i^{keep} denotes the amount the responder returns to sender i when i does not invest, w denotes the initial endowment of sender i, and β measures the marginal utility of income. The amount returned when not investing r_i^{keep} can vary between 0 and the endowment $w = 6\$$ of the responder.

When sender i invests, he foregoes his endowment w which is then doubled and transferred to the responder. As a result, a surplus of w is created when investing. We model the utility of investing as $u_i^{invest} = \beta r_i^{invest} + \theta$, where r_i^{invest} denotes the amount returned by the responder when investing,[10] and θ captures any utility gain

[9]We reject the Null hypothesis that the deviation is equal to zero at the 25th and 75th percentiles for both scenarios (p-value = 0.000 and 0.042 when not investing and p-value = 0.020 and 0.029 when investing).

[10]The amount returned r_i^{invest} by the responder can take a value between 0 and $3w = 18\$$.

coming from some form of other regarding preferences, whether it is a concern for efficiency or altruism.[11] Recent studies suggest that concerns for social efficiency may be particularly important (see Engelmann and Strobel 2004). In terms of our model, this would imply that $\theta > 0$.

We next assume that senders make their decisions by comparing their subjective expected utilities of investing and not investing. The expected utilities of not investing and investing are given by

$$\mathbf{E}\big(u_i^{keep}\big) = \beta\big(w + \mathbf{E}\big(r_i^{keep}\big)\big) + \epsilon_i^{keep}, \tag{1}$$

$$\mathbf{E}\left(u_i^{invest}\right) = \beta\mathbf{E}\left(r_i^{invest}\right) + \theta + \epsilon_i^{invest}, \tag{2}$$

where the expectations are computed with respect to the subjective distribution functions of sender i. To allow for the fact that some senders will make sub-optimal choices, we add standard normal error terms ϵ_i^{invest} and ϵ_i^{keep} to the true expected utilities $\mathbf{E}(u_i^{invest})$ and $\mathbf{E}(u_i^{keep})$, and assume that sender i chooses the option $j \in \{keep, invest\}$ that maximizes $\mathbf{E}(u_i^j) + \epsilon_i^j$ rather than $\mathbf{E}(u_i^j)$.

4 Identification regions of the model parameters

We first characterize the identification region of (β, θ) that is consistent with the observed choice distribution of senders without imposing any information on beliefs. To estimate this region, we first consider the extreme case where all senders expect to receive with probability 1 the highest possible amount when investing ($r^{invest} = 3w$) and the lowest possible amount when not investing ($r^{keep} = 0$). This gives rise to the largest payoff difference between investing and not investing. In this case, the decision rule is to invest when $\mathbf{E}(u_i^{invest}) > \mathbf{E}(u_i^{keep})$, or equivalently

$$\beta(2w) + \theta + \epsilon_i > 0, \tag{3}$$

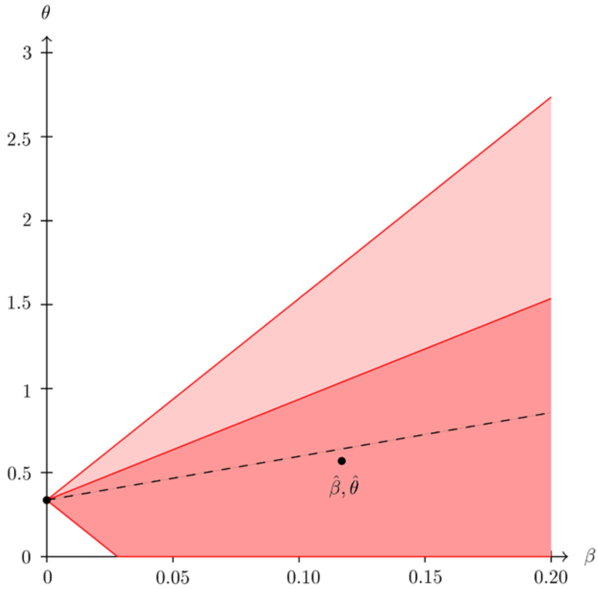
where $\epsilon_i = \epsilon_i^{invest} - \epsilon_i^{keep}$. A second extreme case occurs when all senders expect to receive with probability 1 the lowest amount possible when investing ($r^{invest} = 0$), and the highest possible amount when they do not invest ($r^{keep} = w$). This gives rise to the smallest payoff difference between investing and not investing. In this case, senders i will invest when

$$\beta(-2w) + \theta + \epsilon_i > 0. \tag{4}$$

Assuming that errors ϵ_i are statistically independent of each other and follow a standard normal distribution, aggregating inequalities (3) and (4) across the population yields the following set of inequalities relating the population probability of

[11] The preferences presented here are equivalent to linear altruism (e.g., Andreoni and Miller 2002): $u_i = \alpha x_i + \gamma x_j$ with $\beta = \alpha - \gamma$, $\theta = \gamma \cdot 3w$ where $x_i = r^{invest}$ and $x_j = (3w - r^{invest})$ denote income of player i and j. For the case of not investing, $\gamma = 0$. Our data does not allow us to identify more general preferences (for instance as in Charness and Rabin 2002).

Fig. 3 Estimated identification regions without information on subjective expectations (*both shaded areas*), assuming that $\mathbf{E}(r_i^{invest}) \geq \mathbf{E}(r_i^{keep})$ (*dark shaded area* only), and under rational expectations (*dashed line*). The *point* $(\hat{\beta}, \hat{\theta})$ denotes the parameter estimates obtained using the subjective expectations data



investing to the model parameters

$$\Phi\left(\beta(-2w)+\theta\right) \leq \Pr(invest) \leq \Phi\left(\beta(2w)+\theta\right) \tag{5}$$

where $\Phi(\cdot)$ denotes the standard normal cumulative distribution. The identification region for (β, θ) contains all vectors of parameters that satisfy inequalities (5).

The shaded area in Fig. 3 represents the identification region estimated by replacing $\Pr(invest)$ with the proportion of investments observed in our sample. It is immediate from (5) that θ is point-identified and equal to $\Phi^{-1}(\Pr(invest))$ when expectations have no influence on the decision process ($\beta = 0$). Otherwise, the observed proportion of investments is compatible with any combination of $\beta > 0$ and θ within the shaded area. We can easily see that the identification region of the social preference parameter θ increases with β, the strength of the effect of expectations on investment behavior.

A smaller identification region can be derived by assuming that all senders expect to receive when they invest at least or more than when they do not ($\mathbf{E}(r_i^{invest}) \geq \mathbf{E}(r_i^{keep})$). Under this assumption, inequality (3) remains unchanged as it does not violate the new restriction on beliefs. Inequality (4) on the other hand concerns the lowest possible payoff difference, a difference of 0 under the new restriction ($\mathbf{E}(r_i^{invest}) = \mathbf{E}(r_i^{keep})$). In this case, senders i will invest when

$$\beta(-w)+\theta+\epsilon_i > 0. \tag{6}$$

Aggregating inequalities (3) and (6) across the population produces a new set of inequalities relating the population probability of investing and the model parameters

$$\Phi\left(\beta(-w)+\theta\right) \leq \Pr(invest) \leq \Phi\left(\beta(2w)+\theta\right). \tag{7}$$

The smaller identification region derived from (7) is given by the dark shaded area in Fig. 3. As expected, the new area is a strict subset of the area derived previously as it places much tighter upper bounds of the social preference parameter θ.

Another way to reduce the size of the identification region is to assume that senders have objectively correct (rational) expectations. This would imply that $\mathbf{E}(r_i^{invest})$ and $\mathbf{E}(r_i^{keep})$ both coincide with observed average responder behavior, $\overline{r}^{invest}$ and $\overline{r}^{keep}$, and are common for all players. Then, the identification region is a line, connecting all values of β and θ that solve

$$\Phi\left(\beta(\overline{r}^{invest} - \overline{r}^{keep}) - \beta w + \theta\right) = \Pr(invest). \tag{8}$$

The dashed straight line in Fig. 3 represents the estimated identification region obtained under the assumption that beliefs are rational, estimated by replacing $\overline{r}^{invest}$ and $\overline{r}^{keep}$ with the corresponding sample averages. We see that the assumption of rational expectations does not point identify the model parameters. This follows because all players are assumed to have the same information set. Hence, there is no variation in beliefs across players that would be needed for the point-identification the model parameters.

In our experiment, however, participants have heterogeneous beliefs (see Sect. 2.3). This fact not only contradicts the rational expectation hypothesis but can be exploited to point identify the parameters. To illustrate this, we finally estimate the parameters of our model using the beliefs stated by each sender. To proceed, we replaced the unknown expectations $\mathbf{E}(r_i^{keep})$ and $\mathbf{E}(r_i^{invest})$ in (1) and (2) with expectations approximated using the cubic spline interpolation method proposed in Bellemare et al. (2007).[12] We find that the estimated value of β is 0.117 (standard error = 0.065) and is significant at the 5% level against the one-sided alternative that $\beta > 0$. This suggests that the marginal utility of income is greater than zero. This significant relation also suggests that non-incentivized subjective beliefs can be used to successfully predict behavior. We further find that the other-regarding preference parameter θ is 0.569 (standard error = 0.241) and significant at the 5% level against a two-sided alternative.[13] This suggests that social preferences play a significant role in determining investments in the game. Figure 3 plots this point estimate.

We find that the point estimate lies within the first two identifications regions. The first region was obtained by taking into account all the possible beliefs that respondents could have. Therefore, the point estimate will fall by construction within this zone. The point estimate could fall outside the second identification region if the beliefs of players systematically violated the maintained assumption on beliefs, i.e., that senders will not be worse off when investing ($\mathbf{E}(r_i^{invest}) \geq \mathbf{E}(r_i^{keep})$, used to derive the second identification region. In our data, however, all senders expect to receive from the responder at least as much if they send their endowment than if they keep it.

[12]Cubic spline interpolation allows to approximate expectations with minimal assumptions concerning the shape of the underlying distributions. Bellemare et al. (2007) show that the bias when approximating a subjective mean is negligible given the number of probability questions answered by each sender.

[13]The standard errors are possibly a little conservative as they do not account for noise in the approximated expectations.

Finally, we see that the point estimate using subjective expectations data lies in close proximity to the dashed line representing the identified parameter combinations assuming rational expectations. Moreover, we do not find significant differences between the point estimate and the dashed line.[14] Section 2.3 revealed that the distribution of subjective beliefs is centered around the observed response behavior. This together with the fact that in the simple linear model used here to illustrate the partial identification approach senders' decisions are based on the mean of their subjective expectations probably explains why the dashed line and the point-estimate are close. A model that relies on the whole belief distribution, as for instance a model including risk aversion, would very likely lead to a greater difference between the inferences that one can draw using subjective vs. rational expectations.

5 Conclusion

In this paper we have discussed recent developments in the area of partial identification of econometric models using the stylized example of a binary investment game. We have shown how bounds around model parameters can be derived under various levels of assumptions concerning the beliefs of players. We have also shown how these bounds can be used to assess the validity of using data on beliefs collected without providing players incentives to report them truthfully. Our results provide support for eliciting non-incentivized subjective expectations data: point estimates using these beliefs fall within our most reasonable bounds. More importantly, this paper has highlighted how the partial identification approach can be used to make inferences in a parametric model under weak assumptions about the beliefs of players in the investment game.

Another particularly promising area of future research would be to ask what can be learned about the prevalence of belief dependent preferences such as reciprocity and guilt aversion without information on beliefs. Belief-dependent preferences typically involve second-order beliefs, that is beliefs of players over the distribution of beliefs of other players. Elicitation of second-order beliefs is complicated by several factors. First, the task is cognitively more demanding than collecting data on first-order beliefs. Second, consensus effects may lead to a spurious correlation between decisions and stated second-order beliefs, thus biasing the quantitative importance of these preferences (see e.g., Ellingsen et al. 2010, Bellemare et al. 2010). The tools of partial identification may provide a way to learn about the relevance of these preferences while avoiding the potential problems posed by elicitation of second-order beliefs.

The application of partial identification analysis in experimental economics goes beyond the partial observability of player beliefs. For instance, in many common

[14] We estimated by bootstrap the 95% confidence region around our point estimate as well as a 95% confidence region around the dashed line by bootstrap. In particular, we generated 1000 bootstrap samples, sampling with replacement the decision and beliefs of senders. We computed for each bootstrap sample the point estimate as well as the dashed line. Computing both estimates using the same samples allows us to control for the correlation between the estimated dashed line and the point estimates that both rely on the same data. We find that both confidence regions overlap substantially.

experiments, interval responses are elicited (as opposed to point-valuations) using multiple price lists, as discussed by Andersen et al. (2006). Multiple price lists are frequently used in experiments to measure preference parameters, willingness to pay, or discount rates. Interval regressions used to analyze interval responses elicited using multiple price lists typically impose sufficiently strong parametric assumptions on the distribution of unobservables to point estimate the model parameters (see e.g., Coller and Williams 1999). The tools of partial identification, on the other hand, allow researchers to bound the model parameters under minimal assumptions about the location of the true valuations within the intervals of each respondent. Manski and Tamer (2002) show how bounds around model parameters can be derived in this setting. The estimated bounds can thus be contrasted with point estimates obtained using stronger assumptions, thus providing a basis for model specification testing.

Finally, partial identification can also be useful to understand the preferences of players in games with multiple equilibria. Multiplicity of equilibria severely complicates point estimation of the heterogeneity in preferences of players. One way to point identify preferences has been to assume an equilibrium selection procedure (e.g. randomly selecting one of the possible equilibriums). Ciliberto and Tamer (2009) show how bounds can be placed around the choice probabilities in discrete games without imposing any equilibrium selection procedure. As we have stressed in this paper, these bounds can then be used to perform meaningful inferences on the model parameters characterizing the decision rules of players in the game.

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