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Modeling the dynamics of contributions and beliefs in repeated public good games

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Abstract

I estimate a simultaneous equations model of contributions and beliefs in a repeated public good game, providing causal estimates of the effect of beliefs on contributions and the effect of contributions on beliefs, also known as the "projection bias."

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1. Introduction

The convention in the literature on conditional cooperation in repeated public good games is modeling contributions as a function of beliefs (Croson, 2007; Neugebauer *et al.*, 2009; Fischbacher and Gaechter, 2010; Gaechter and Renner, 2010) and beliefs as a function of variables from the previous round (Neugebauer *et al.*, 2009; Fischbacher and Gaechter, 2010), implicitly assuming that in each round, beliefs are exogenous to contribution decisions. Avoiding such an exogeneity assumption, Smith (2013) uses instrumental variables (IV) to estimate the contemporaneous causal effect of beliefs on contributions.[1] He does not, however, model the dynamic relationship between contributions and beliefs.

In this note, I model the dynamics of contributions and beliefs about the average contributions of others using a system of simultaneous equations that captures the simultaneity that arises from contributions and beliefs being jointly caused by each other and variables from the previous round. The tendency for actions to cause beliefs is often called the projection bias or (false) consensus effect, and it occurs when people project their behavior on to others (Offerman, Sonnemans and Schram, 1996; Engelmann and Strobel, 2000).

I obtain causal estimates of the effect of beliefs on contributions and the effect of contributions on beliefs using an empirical strategy that is a straightforward application of a simple econometric technique, but to my knowledge, has not previously been used for analyzing data from an experiment with belief elicitation.[2] As such, I contribute to the literature by providing a new reduced-form alternative to estimating the joint determination of actions and beliefs using structural methods (Bellamare, Kroeger and van Soest, 2008; Bellamare, Sebald and Strobel, 2011). I also contribute by presenting the first causal estimate of which I am aware on the magnitude of the projection bias.

2. Experiment Design

The primary analysis is conducted using the data from Smith (2013), a 20 round, linear public good game with incentive compatible belief elicitation in each round. Subjects were matched in fixed groups of four. In each round, they were given 10 lab dollars (LD; later converted to USD at a rate of 1 LD = 0.05 USD) and chose contributions to the public good, keeping the rest of the money for themselves. As proceeds from the public good, each subject received 0.5 times the sum of contributions, making the payoffs:

$$\pi_i = 10 - c_i + 0.5 \sum_{j=1}^{4} c_j \tag{1}$$

where c_i was the contribution of subject i and subject i's group members are indexed by j. After each round, subjects were told the average amount contributed by the other members

[1] Bicchieri and Xiao (2009), and Costa-Gomes, Huck and Weizsaecker (2014) use IV techniques for estimating the causal effects of beliefs on actions in one-shot games.

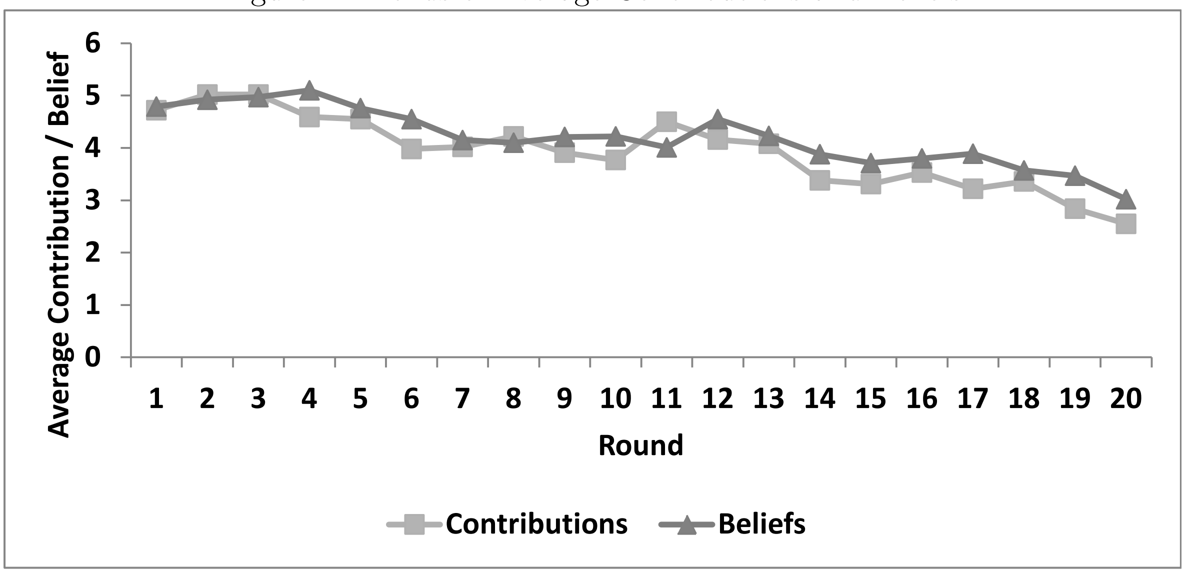
[2] Cason, Savikhin and Sheremeta (2012) use simultaneous equations for analyzing decisions in simultaneous coordination games. Savikhin and Sheremeta (2013) conduct a similar analysis with simultaneous competitive and cooperative games. McCarter, Samak and Sheremeta (2014) is about simultaneous social dilemmas, but they do not report using simultaneous equations estimation.

of their groups, and their payoffs from the public good game and for the accuracy of their beliefs. For a more detailed explanation of the experiment, please consult Smith (2013).

3. Results

Sixty-four subjects participated in the experiment, generating 1,280 observations. The average contribution was 3.94 (std. dev. 2.98) and the average belief was 4.19 (std. dev. 1.91). Average contributions and beliefs in each round are plotted in Figure 1.

Figure 1: Trends of Average Contributions and Beliefs



I model contributions and beliefs using the following system of simultaneous equations:

$$contribution = \beta_{10} + \gamma_1 belief + \beta_{11} contribution_{-1} + \beta_{12} round + \varepsilon_1 \quad (2)$$

$$belief = \beta_{20} + \gamma_2 contribution + \beta_{21} belief_{-1} + \beta_{22} average\, others_{-1} + \beta_{23} round + \varepsilon_2 \quad (3)$$

The contribution equation is consistent with previous literature (Croson, 2007; Neugebauer *et al.*, 2009; Fischbacher and Gaechter, 2010; Gaechter and Renner, 2010; Smith, 2013).[3] The belief equation, in contrast, is different from previous literature because contributions are added as a regressor. This captures any tendency for contributions to cause beliefs. I exclude lagged beliefs from the contribution equation because a variety of exploratory regressions (not shown, but available upon request) fail to provide any evidence that lagged beliefs have a direct effect on contributions. Lagged contributions are excluded from the belief equation for a parallel reason. I exclude the lagged average contributions of others from the contribution equation in light of previous findings that they do not have a significant effect when one controls for beliefs (Neugebauer *et al.*, 2009; Smith, 2013).[4]

[3]For a paper on modeling contributions as an autoregressive process, see Smith (2012).

[4]Croson (2007), Fischbacher and Gaechter (2010), and Gaechter and Renner (2010) exclude lagged average contributions of others in their regressions of contributions on beliefs.

I first estimate each equation using OLS (models (I) and (II) in Table 1).[5] In model (I), beliefs have a large effect on contributions, consistent with previous literature (Croson, 2007; Neugebauer *et al.*, 2009; Fischbacher and Gaechter, 2010; Gaechter and Renner, 2010; Smith, 2013). Lagged contributions are also significant. In model (II), contributions have a highly significant effect on beliefs, providing preliminary evidence on the projection bias. Lagged beliefs and lagged average contributions of others are also significant.

Table 1: Regressions of Contributions and Beliefs - Data from Smith (2013)

	(I)	(II)	(III)	(IV)
dependent variable:	*contribution*	*belief*	*contribution*	*belief*
contribution	-	0.18***	-	0.15*
		(0.02)		(0.08)
belief	0.77***	-	0.39***	-
	(0.08)		(0.09)	
$contribution_{-1}$	0.12**	-	0.17***	-
	(0.04)		(0.04)	
$belief_{-1}$	-	0.18***	-	0.18***
		(0.03)		(0.03)
$average\ others_{-1}$	-	0.53***	-	0.54***
		(0.04)		(0.03)
round	-0.03*	0.00	-0.06***	0.00
	(0.01)	(0.01)	(0.02)	(0.01)
constant	0.53	0.57***	2.27***	0.69
	(0.32)	(0.19)	(0.65)	(0.55)
subject dummies	yes	yes	yes	yes
method	OLS	OLS	2SLS	2SLS
subjects	64	64	64	64
rounds	2-20	2-20	2-20	2-20
n	1,216	1,216	1,216	1,216
R^2	0.29	0.79	0.55	0.84
Hausman p	-	-	0.00	0.67
Sargan p	-	-	0.17	-
Basmann p	-	-	0.19	-
1st stage F-stat	-	-	165.08	13.27

Notes: Standard errors adjusted for clustering at the group level are reported in parentheses.
***: $p < .01$; **: $p < .05$; *: $p < .1$

[5] Subject dummies control for subject-specific fixed effects. Smith (2013) reports that this gives very similar results to the method of Arellano and Bond (Arellano and Bond, 1991), a preferable way of estimating autoregressive models that unfortunately cannot be used within a system of equations. All models are estimated using least squares. Tobit results are very similar, but the least squares results a slightly more conservative in terms of the significance of the estimates. Tobit of course involves the implicit assumption that the dependent variable has a censored normal distribution. The censoring is obvious, but the normality is not so clear. Least squares does not invoke this kind of distributional assumption.

Next, to address any simultaneity between contributions and beliefs, I estimate each equation using 2SLS (models (III) and (IV)). I estimate the contribution equation (model (III)) using the excluded variables ($belief_{-1}$ and $average\,others_{-1}$) as instruments for beliefs. The causal effect of beliefs (0.39) is much smaller than the OLS estimate (0.77) from model (I). A Hausman test ($p = 0.00$) indicates that beliefs are endogenous, and Sargan ($p = 0.17$) and Basmann ($p = 0.19$) tests fail to reject the null hypothesis that the instruments are valid. The first-stage F-statistic (165.08) indicates that the instruments are not weak.[6]

I estimate the belief equation (model (IV)) using lagged contributions as an instrument for contributions. The causal estimate of the projection bias is that unit increases in contributions increase beliefs by 0.15. A Hausman test ($p = 0.67$) fails to reject the null hypothesis that contributions are exogenous, suggesting that OLS (model (II)) provides an accurate estimate of the projection bias. Sargan and Basmann tests are not possible since there is only one instrument, which the first-stage F-statistic indicates is not weak.[7]

4. Replication

Since many repeated public good games are ten rounds instead of 20, the first replication exercise is conducting the analysis after truncating the data at ten rounds (see Table 2). The results are generally very similar. For example, in model (I), beliefs have a large effect on contributions and in model (II), contributions have a significant effect on beliefs. In model (III), the causal effect of beliefs on contributions is much smaller than the OLS estimate from model (I). However, there is one critical difference from Table 1: since lagged contributions do not have a significant effect on contributions (see model (I)), they are a weak instrument for contributions in model (IV), and the estimate of the causal effect of contributions on beliefs is imprecise (has a high standard error).[8] The causal estimate of the projection bias in model (IV) is as a result not statistically significant.

To determine if this is a recurring challenge, I also conduct the analysis using the data from Gaechter and Renner (2010), who ran a ten round game with fixed groups of four.[9] They had three treatments: incentivized beliefs, non-incentivized beliefs and no beliefs.

The results using the data from the incentivized beliefs treatment are presented in Table 3, which matches Table 2 very closely. In model (IV), lagged contributions are once again a weak instrument for contributions and the causal estimate of the projection bias is not statistically significant (this time, in spite of being large in magnitude). The results using the non-incentivized beliefs treatment are reported in Table 4. In model (III), lagged beliefs are a weaker instrument for beliefs than in the previous analysis (Tables 1-3), and the Hausman test that beliefs are endogenous is not significant ($p = 0.27$). In model (IV), lagged

[6]These results are as in Smith (2013), where the focus is estimating a contribution equation. It is the simultaneous equations model and estimation of the belief equation (which includes the projection bias) that go beyond the work of Smith (2013), and are the main contributions of this note.

[7]3SLS (the efficient estimator) gives nearly identical results.

[8]The change in the effect of lagged contributions on contributions compared to the Table 1 results is predicted by Nickell (1981), who shows that the bias of fixed effects estimation of autoregressive models is decreasing in the length of the panel.

[9]The marginal per capita return (MPCR) from the public good was 0.4 and the subjects were given 20 tokens to start each round.

contributions are a weak instrument for contributions and the estimate of the projection bias is not significant.

Table 2: Regressions of Contributions and Beliefs - Truncated Data from Smith (2013)

	(I)	(II)	(III)	(IV)
dependent variable:	*contribution*	*belief*	*contribution*	*belief*
contribution	-	0.20***	-	-0.14
		(0.03)		(0.59)
belief	0.76***	-	0.36***	-
	(0.07)		(0.07)	
$contribution_{-1}$	0.02	-	0.06	-
	(0.05)		(0.06)	
$belief_{-1}$	-	0.14**	-	0.17***
		(0.05)		(0.06)
$average\,others_{-1}$	-	0.60***	-	0.68***
		(0.04)		(0.12)
round	-0.06*	0.00	-0.11**	-0.04
	(0.03)	(0.02)	(0.04)	(0.08)
constant	1.14**	0.35	2.59***	2.45
	(0.48)	(0.32)	(0.57)	(4.13)
subject dummies	yes	yes	yes	yes
method	OLS	OLS	2SLS	2SLS
subjects	64	64	64	64
rounds	2-10	2-10	2-10	2-10
n	576	576	576	576
R^2	0.26	0.80	0.58	0.72
Hausman p	-	-	0.00	0.41
Sargan p	-	-	0.57	-
Basmann p	-	-	0.59	-
1st stage F-stat	-	-	91.01	0.61

Notes: Standard errors adjusted for clustering at the group level are reported in parentheses.
***: $p < .01$; **: $p < .05$; *: $p < .1$

Table 3: Regressions of Contributions and Beliefs - Data from Gaechter and Renner (2010) - Incentivized Beliefs Treatment

	(I)	(II)	(III)	(IV)
dependent variable:	*contribution*	*belief*	*contribution*	*belief*
contribution	-	0.22***	-	0.42
		(0.03)		(0.55)
belief	0.81***	-	0.58***	-
	(0.07)		(0.09)	
$contribution_{-1}$	0.02	-	0.04	-
	(0.07)		(0.07)	
$belief_{-1}$	-	0.20***	-	0.18*
		(0.05)		(0.10)
$average\ others_{-1}$	-	0.50***	-	0.43**
		(0.04)		(0.21)
round	-0.05	-0.06**	-0.13	-0.03
	(0.08)	(0.03)	(0.09)	(0.13)
constant	1.62	1.06	4.35***	0.02
	(0.96)	(0.67)	(1.10)	(3.38)
subject dummies	yes	yes	yes	yes
method	OLS	OLS	2SLS	2SLS
subjects	64	64	64	64
rounds	2-10	2-10	2-10	2-10
n	576	576	576	576
R^2	0.45	0.83	0.73	0.86
Hausman p	-	-	0.02	0.72
Sargan p	-	-	0.50	-
Basmann p	-	-	0.52	-
1st stage F-stat	-	-	148.64	0.49

Notes: Standard errors adjusted for clustering at the group level are reported in parentheses.
***: $p < .01$; **: $p < .05$; *: $p < .1$

Table 4: Regressions of Contributions and Beliefs - Data from Gaechter and Renner (2010) - Non-incentivized Beliefs Treatment

	(I)	(II)	(III)	(IV)
dependent variable:	*contribution*	*belief*	*contribution*	*belief*
contribution	-	0.27***	-	0.72
		(0.04)		(0.49)
belief	0.55***	-	0.35***	-
	(0.10)		(0.13)	
$contribution_{-1}$	0.07	-	0.08	-
	(0.06)		(0.06)	
$belief_{-1}$	-	0.06	-	0.01
		(0.07)		(0.08)
$average\ others_{-1}$	-	0.50***	-	0.42***
		(0.06)		(0.11)
round	-0.23**	-0.13*	-0.36***	0.08
	(0.08)	(0.07)	(0.08)	(0.21)
constant	3.27**	2.50*	5.17***	-0.91
	(1.18)	(1.20)	(1.72)	(4.77)
subject dummies	yes	yes	yes	yes
method	OLS	OLS	2SLS	2SLS
subjects	68	68	68	68
rounds	2-10	2-10	2-10	2-10
n	612	612	612	612
R^2	0.41	0.63	0.67	0.63
Hausman p	-	-	0.27	0.28
Sargan p	-	-	0.51	-
Basmann p	-	-	0.54	-
1st stage F-stat	-	-	26.49	1.61

Notes: Standard errors adjusted for clustering at the group level are reported in parentheses.
***: $p < .01$; **: $p < .05$; *: $p < .1$

5. Summary

I present a method for estimating the dynamics of contributions and beliefs in repeated public good games using a simultaneous equations model. I find that high correlation between contributions and beliefs is attributable to both beliefs causing contributions and contributions causing beliefs, also known as the projection bias. My causal estimate of the magnitude of the projection bias is that unit increases in contributions increase beliefs by 0.15.

I find that the simultaneous equations approach works best with longer panels of data (20 rounds is better than ten) and incentivized belief elicitation, providing a rationale for conducting more repetitions in repeated game experiments and doing incentive compatible belief elicitation. With these caveats, it seems that the method could be applied to data from any repeated game with symmetric players and belief elicitation about the actions of others.

References

Arellano, M. and S. Bond (1991). "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations." *Review of Economic Studies* **58**, 277-97.

Bellamare, C., S. Kroeger and A. van Soest (2008). "Measuring Inequity Aversion in a Heterogeneous Population Using Experimental Decisions and Subjective Probabilities." *Econometrica* **76**, 815-39.

Bellamare, C., A. Sebald and M. Strobel (2011). "Measuring the Willingness to Pay to Avoid Guilt: Estimation Using Equilibrium and Stated Belief Models." *Journal of Applied Econometrics* **26**, 437-53.

Bicchieri, C. and E. Xiao (2009). "Do the Right Thing: But Only if Others Do So." *Journal of Behavioral Decision Making* **22**, 191-208.

Cason, T., A. Savikhin and R. Sheremeta (2012). "Behavioral Spillovers in Coordination Games." *European Economic Review* **56**, 233-45.

Costa-Gomes, M., S. Huck and G. Weizsaecker (2014). "Beliefs and Actions in the Trust Game: Creating Instrumental Variables to Estimate the Causal Effect." *Games and Economic Behavior* **88**, 298-309.

Croson, R. (2007). "Theories of Commitment, Altruism and Reciprocity: Evidence from Linear Public Goods Games." *Economic Inquiry* **45**, 199-216.

Engelmann, D. and M. Strobel (2000). "The False Consensus Effect Disappears if Representative Information and Monetary Incentives Are Given." *Experimental Economics* **3**, 241-60.

Fischbacher, U. and S. Gaechter (2010). "Social Preferences, Beliefs, and the Dynamics of Free Riding in Public Goods Experiments." *American Economic Review* **100**, 541-56.

Gaechter, S. and E. Renner (2010). "The Effects of (Incentivized) Belief Elicitation in Public Goods Experiments." *Experimental Economics* **13**, 364-77.

McCarter, M., A. Samak and R. Sheremeta (2014). "Divided Loyalists or Conditional Cooperators? Creating Consensus about Cooperation in Multiple Simultaneous Social Dilemmas." *Group and Organization Management* **39**, 744-71.

Neugebauer, T., J. Perote, U. Schmidt and M. Loos (2009). "Selfish-Biased Conditional Cooperation: On the Decline of Contributions in Repeated Public Goods Experiments." *Journal of Economic Psychology* **30**, 52-60.

Nickell, S. (1981). "Biases in Dynamic Models with Fixed Effects." *Econometrica* **49**, 1417-26.
Offerman, T., J. Sonnemans and A. Schram (1996). "Value Orientations, Expectations and Voluntary Contributions in Public Goods." *Economic Journal* **106**, 817-45.
Savikhin, A. and R. Sheremeta (2013). "Simultaneous Decision-Making in Competitive and Cooperative Games." *Economic Inquiry* **51**, 1311-23.
Smith, A. (2013). "Estimating the Causal Effect of Beliefs on Contributions in Repeated Public Good Games." *Experimental Economics* **16**, 414-25.
Smith, A. (2012). "Comment on Social Preferences, Beliefs, and the Dynamics of Free Riding in Public Good Experiments." *Economics Bulletin* **32**, 923-31.