You Owe Me

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Online Appendix

Appendix A: Proofs

Before proving Proposition 1 we have to properly define the three types of social preferences that we consider.

(i) *Altruism* (*utilitarianism*): A decision maker is utilitarian if her utility function is strictly increasing in $(m^X + m^Y + m^C)$, i.e., $\dfrac{\partial U^{DM}(m^{DM}, m^X, m^Y, m^C)}{\partial(m^X + m^Y + m^C)} > 0$.

(ii) *Maximin preferences*: The decision maker has maximin preferences if

$$U^{DM} = (1-\lambda)\cdot m^{DM} + \lambda \cdot \min\{m^{DM}, m^X, m^Y, m^C\},$$

where $0 < \lambda < 1$. Thus, if m^{DM} is unaffected by DM's decision, she maximizes the payoff of the player who is worst off in the group.[1]

(iii) *Inequality aversion*: The decision maker is inequality averse if she wants to minimize the payoff differences between her own payoff and the payoffs of each of the other players (Fehr and Schmidt, 1999), i.e.,

$$U^{DM} = m^{DM} - \frac{\alpha}{3}\sum_j \min\{m^j - m^{DM}, 0\} - \frac{\beta}{3}\sum_j \min\{m^{DM} - m^j, 0\} \text{ with } j \in \{X, Y, C\},$$

where $0 < \beta \leq \alpha$.[2] Note that the material payoff of the decision maker is 20 plus the gift, which is (weakly) greater than the material payoff that any other player can get in any state of the world. Thus, like an altruist, an inequality-averse decision maker always wants to increase the material payoffs of the other players.

Proof of Proposition 1: We consider the three cases of the proposition in turn. Note that in all

[1] Charness and Rabin (2002) consider the case where the decision maker maximizes a weighted sum of her own payoff, the sum of all payoffs, and the payoff of the worst off in the group. This is a convex combination of utilitarianism and maximin preferences. The extension of our results to this case is straightforward.

[2] An alternative formulation is that she wants her own payoff to be as close as possible to the average payoff of all players (Bolton and Ockenfels, 2000), i.e., $U^{DM} = U^{DM}(m^{DM}, m^{DM}/\Sigma_j m^j)$ with $j \in \{DM, X, Y, C\}$ and where $\partial U^{DM}/\partial m^j > 0$ iff $m^{DM}/\Sigma_j m^j > 1/4$. This does not affect our results.

cases the decision maker cannot affect her own material payoff.

(a) *Baseline Treatment*. DM's payoff is always weakly greater than the realized payoff of the client. Her own monetary payoff is unaffected by her decision. Thus, all three outcome-based preference models predict that DM maximizes the payoff of the client.[3]

(b) *Gift Treatment, gift given*: The distribution of material payoffs of the two producers is unaffected by DM's choice. Thus, she favors the client as in (a).

(c) *Gift Treatment, gift not given*: If producer *X* did not pass on the gift, DM can affect the payoff distribution of the producers. If she chooses product *X* the material payoffs of the producers are (17,0), if she chooses *Y*, they are (1,16). If she is utilitarian or inequality averse, she is indifferent between these two distributions – in the case of utilitarian preferences because the sum of payoffs is unaffected, in the case of inequality aversion because DM's utility depends on the average difference between her payoff and the payoff of other players' who are behind, regardless of the distribution among those players. Thus, she maximizes the payoff of the client. However, if she has maximin preferences, she favors producer *Y* because

$$20+\min\left\{20,1,16,m^{C}(Y)\right\}>20+\min\left\{20,17,0,m^{C}(X)\right\}$$
$$\Leftrightarrow \qquad 1>0,$$

where $m^{C}(i)>0$ is the client's expected payoff if product $i\in\{X,Y\}$ is chosen. ***Q.E.D.***

<u>Proof of Proposition 2</u>: In a pooling equilibrium all producers choose the same strategy. Thus, on the equilibrium path DM does not learn anything about the type of the (potential) gift giver. If DM is kind, she maximizes the sum of payoffs since, in a pooling equilibrium, all other players have the same expected weight in her utility function. Hence, a kind DM favors the client. If DM is selfish, she is indifferent and, hence, also favors the client in equilibrium, as assumed in Section 4.

For the proof of the second part of the proposition, let p^{gg} denote the probability that DM chooses product *X* if the gift was given, and p^{gng} the probability that DM chooses *X* if the gift was not given. A selfish producer *X* keeps the gift only if

$$1+p^{gng}\cdot 16\geq p^{gg}\cdot 16 \ .$$

Thus, any equilibrium in which the selfish type keeps the gift with positive probability must have

[3] With altruistic and inequality averse preferences this prediction is unique. If DM has maximin preferences he is indifferent which product to choose.

$p^{gg} - p^{gng} \leq 1/16$. Thus, if $p^{gg} - p^{gng} > 1/16$, producer X cannot signal that he is the kind type by giving the gift because the selfish type will mimic him. ***Q.E.D.***

Proof of Proposition 3: At stage 1 producer X chooses whether to send the gift (G) or not to send the gift (N). Then DM decides whether to choose X's product (X) or the product that yields the highest expected payoff for the client (C). Since the role of the gift giver was randomly allocated, we maintain that the parties assign a probability of 50 percent to having the better product. The expected payoffs are given in the normal form of this sequential game:

DM \ *X*	*XX*	*XC*	*CX*	*CC*
G	16, 22	16, 22	8,22	8, 22
N	17, 20	9, 20	17,20	9, 20

For players $i \in \{X, DM\}$, let a_i denote player i's strategy, b_{ij} player i's belief about the strategy chosen by player j (first-order belief), and c_{iji} player i's belief what player j believes about i's strategy (second-order belief), with $j \neq i$. Player i's expected utility is given by

$$U^i(a_i, b_{ij}, c_{iji}) = m^i(a_i, b_{ij}) + n_i \cdot \kappa_{ij}(a_i, b_{ij}) \cdot \lambda_{iji}(b_{ij}, c_{iji}).$$

The first term is i's expected monetary payoff. The second term is i's reciprocity payoff. Here, the parameter $n_i \geq 0$ reflects how much i cares about the perceived kindness of player j, $\lambda_{iji}(b_{ij}, c_{iji})$. The kindness of player i is given by the function

$$\kappa_{ij}(a_i, b_{ij}) = m^j(a_i, b_{ij}) - m^j_{e_i}(b_{ij}).$$

This is the payoff that player i "gives" to player j by choosing a_i assuming that j chooses b_{ij}, minus the "equitable" payoff of j which is defined as the average of the maximum and the minimum payoff that player i can "give" to player j (assuming that j chooses b_{ij}):

$$m^j_{e_i}(b_{ij}) = \frac{\max_{a_i}\{m^j(a_i, b_{ij})\} + \min_{a_i}\{m^j(a_i, b_{ij})\}}{2}.$$

The perceived kindness of player j is given by the function

$$\lambda_{iji}(b_{ij}, c_{iji}) = m^i(b_{ij}, c_{iji}) - m^i_{e_j}(c_{iji}).$$

This is the payoff that player i believes that player j is giving to him minus the "equitable" payoff (average of maximum and minimum payoff) that player *j* can give to player *i*. Note that if player *i* expects *j* to give him less than the equitable payoff, *j*'s perceived kindness is negative, so *i* wants to give player *j* also less than the equitable payoff, and vice versa. A strategy profile $a^*=$ $(a_i*)_{i\in\{X,DM\}}$ is a sequential reciprocity equilibrium (SRE) if a_i* maximizes $U^i(a_i, b_{ij}, c_{iji})$ and if $b_{ij} = a_j*$ and $c_{iji} = a_i*$.[4]

If *X* chooses *G*, then DM always gets 22. If *X* chooses *N*, then she always gets 20. The equitable payoff for DM, $m_{e_X}^{DM}(b_{X,DM})$, is 21. Thus, no matter what DM believes, if *X* chooses *G*, we have $\lambda_{DM,X,DM} = 22 - 21 = 1$, i.e., DM perceives *X*'s intentions as "kind." Similarly, if *X* chooses *N*, we have $\lambda_{DM,X,DM} = 20 - 21 = -1$, and DM perceives *X*'s intention as "unkind."

We now show that it is part of an SRE that *X* chooses *G* and DM chooses *XC*. We know already that, if producer *X* chooses *G*, then DM must perceive this as kind, so DM wants to reciprocate and to choose a kind action as well. By choosing action *X*, DM gives producer *X* a payoff of 16; by choosing *C*, she gives producer *X* an expected payoff of 8. The equitable payoff is (16+8)/2=12. Thus, by choosing *X*, DM gets $U^{DM}(X, G, XC) = 22 + n_{DM} \cdot (16\text{-}12) \cdot (22\text{-}21) = 22 + 4n_{DM}$; by choosing *C*, she obtains $U^{DM}(C, G, XC) = 22 + n_{DM} \cdot (8\text{-}12) \cdot (22\text{-}21) = 22 - 4n_{DM}$. Hence, for any $n_{DM} > 0$ choosing action *X* is optimal.

Consider now producer *X*. He believes that DM chooses the strategy *XC*. Furthermore, he believes that DM believes that *X* chooses *G*. Thus, producer *X* believes that DM is kind, because she reacts with *X* to *G* and gives him a payoff of 16 rather than 8 ($\lambda_{X,DM,X} = 16 - 12 = +4$). Therefore player *X* wants to be kind as well. If he passes on the gift, his utility is $U^X(G, XC, G) = 16 + n_X \cdot (22\text{-}21) \cdot (16\text{-}12) = 16 + 4n_X$. If he does not pass on the gift, he gets $U^X(N, XC, G) = 9 + n_X \cdot (20\text{-}21) \cdot (16\text{-}12) = 9 - 4n_X$. Thus, for any $n_X > 0$ choosing *G* is indeed optimal.

Finally, we show that it is part of a SRE that *X* chooses *N* and DM chooses *XC*. We know already that if *X* chooses *N*, then DM must perceive this as unkind, so DM wants to reciprocate and choose an unkind action as well. By choosing action *C*, DM gives *X* a payoff of 1+8=9; by choosing X, she gives *X* a payoff of 1+16=17. The equitable payoff is (17+9)/2=13. Thus, by choosing *C*, DM gets $U^{DM}(C, N, XC) = 20 + n_{DM} \cdot (9\text{-}13) \cdot (20\text{-}21) = 20 + 4n_{DM}$; by choosing *X*, she obtains $U^{DM}(X, N, XC) = 20 + n_{DM} \cdot (17\text{-}13) \cdot (20\text{-}21) = 20 - 4n_{DM}$. Hence, for any $n_{DM} > 0$ choosing *C* is optimal.

Consider now producer *X*. He believes that DM chooses the strategy *XC*. Furthermore, he

[4] See Dufwenberg and Kirchsteiger (2004) for more details and a discussion of the notion of SRE.

believes that DM believes that X chooses N. Thus, X believes that DM is unkind, because she reacts with C to N and gives him a payoff of 9 rather than 17 ($\lambda_{X,DM,X} = 9-13 = -4$). Therefore, player X wants to be unkind as well. If she does not pass on the gift, she gets $U^X(N, XC, N) = 9 + n_X \cdot (20\text{-}21) \cdot (9\text{-}13) = 9 + 4n_X$. If she passes on the gift, she gets $U^X(G, XC, N) = 17 + n_X \cdot (22\text{-}21) \cdot (9\text{-}13) = 17\text{-}4n_X$. Thus, if $n_X > 1$, choosing N is indeed optimal. ***Q.E.D.***

Proof of Proposition 4: W.l.o.g. assume that, if DM is indifferent between X and Y and also $m^C(X) = m^C(Y)$, then DM chooses X. Let $\Delta = m^C(Y) - m^C(X)$ denote the disadvantage of product X relative to product Y (in terms of expected payoff to the client).

(i) Suppose that producer X passed on the gift. If X is the weakly better product ($\Delta \leq 0$) DM clearly chooses X, both in the Gift Treatment (GT) and in the No Externality Treatment. If X is the worse product ($\Delta > 0$) DM chooses X in GT if and only if

$$22 + \alpha \cdot 0 + k \cdot \alpha \cdot 16 + \alpha \cdot m^C(X) > 22 + \alpha \cdot 16 + k \cdot \alpha \cdot 0 + \alpha \cdot [m^C(X) + \Delta]$$

$$\Leftrightarrow \quad k \cdot \alpha \cdot 16 > \alpha \cdot 16 + \alpha \cdot \Delta \;\; \Leftrightarrow \quad k > 1 + \frac{\Delta}{16}.$$

And in the No Externality Treatment (NET), DM chooses X if and only if

$$m^{DM}(X) + 2 + \alpha \cdot 0 + k \cdot \alpha \cdot 16 > m^{DM}(X) + \Delta + 2 + \alpha \cdot 16 + k \cdot \alpha \cdot 0$$

$$\Leftrightarrow \quad k \cdot \alpha \cdot 16 > \alpha \cdot 16 + \Delta \quad \Leftrightarrow \quad k > 1 + \frac{\Delta}{16\alpha}.$$

Hence, if product X is strictly worse ($\Delta > 0$), DM still chooses X for large enough k, and she is more likely to do so in GT than in NET since the k-threshold is lower: $1 + \frac{\Delta}{16} < 1 + \frac{\Delta}{16\alpha}$ for all $0 < \alpha < 1$.

(ii) Suppose now that producer X did not pass on the gift. Then, in the Gift Treatment (GT), DM chooses X if and only if

$$20 + l \cdot \alpha \cdot 17 + \alpha \cdot 0 + \alpha \cdot m^C(X) \geq 20 + l \cdot \alpha \cdot 1 + \alpha \cdot 16 + \alpha \cdot [m^C(X) + \Delta]$$

$$\Leftrightarrow l \cdot 16\alpha \geq 16\alpha + \alpha\Delta \quad \Leftrightarrow \quad l \geq 1 + \frac{\Delta}{16},$$

if X is the (weakly) better product ($\Delta \leq 0$). The inequality cannot hold if X is the worse product ($\Delta > 0$) because $0 \leq l \leq 1$.

In the No Externality Treatment (NET), DM chooses X if and only if

$$m^{DM}(X)+l\cdot\alpha\cdot 17+\alpha\cdot 0\geq m^{DM}(X)+\Delta+l\cdot\alpha\cdot 1+\alpha\cdot 16$$
$$\Leftrightarrow l\cdot 16\alpha\geq\Delta+16\alpha \quad\Leftrightarrow\quad l\geq 1+\frac{\Delta}{16\alpha},$$

if X is the (weakly) better product ($\Delta\leq 0$). Again, the inequality cannot hold if X is the worse product ($\Delta > 0$).

If product X is weakly better than Y ($\Delta\leq 0$), then, with $0\leq l\leq 1$, the inequalities hold for large enough l and, with $1+\frac{\Delta}{16}\geq 1+\frac{\Delta}{16\alpha}$ for $\Delta\leq 0$, it is less likely to hold in the GT than in the NET.

Q.E.D.

Proposition 5. Consider decision makers with social preferences satisfying Assumption 1.

(i) Suppose that producer X did pass on the gift. If product X is (weakly) better than product Y, DM always chooses X in the GT and the IT. If product X is strictly worse, DM may still choose X, and she is most likely to do so in IT with<u>out</u> profit sharing, less likely to do so in GT, and least likely to do so in IT with profit sharing.

(ii) Suppose that producer X did not pass on the gift. If X is (weakly) worse than Y, DM always chooses Y in the GT and the IT. If X is strictly better, DM may still choose Y, and she is most likely to do so in IT with profit sharing, less likely to do so in GT, and least likely to do so in IT without profit sharing.

<u>Proof of Proposition 5:</u> W.l.o.g. assume that, if DM is indifferent between X and Y and if $m^C(X) = m^C(Y)$, then DM chooses X.

(i) Suppose that the client offered profit sharing and the producer X passed on the gift. Clearly, if X is at least weakly better than Y (i.e. $\Delta\leq 0$), then DM chooses X, which increases her own material payoff and is good for the gift giver and the client. If $\Delta > 0$, DM chooses X if and only if

$$22+0.1\cdot m^C(X)+k\cdot\alpha\cdot 16+\alpha\cdot 0+k\cdot\alpha\cdot 0.95\cdot m^C(X)$$
$$>22+0.1\cdot(m^C(X)+\Delta)+k\cdot\alpha\cdot 0+\alpha\cdot 16+k\cdot\alpha\cdot 0.95\cdot(m^C(X)+\Delta)$$
$$\Leftrightarrow\quad k\cdot\alpha\cdot 16>0.1\cdot\Delta+\alpha\cdot 16+k\cdot\alpha\cdot 0.95\cdot\Delta$$
$$\Leftrightarrow\quad k\cdot\alpha\cdot(16-0.95\cdot\Delta)>16\alpha+0.1\Delta$$
$$\Leftrightarrow\quad k>\frac{16\alpha+0.1\cdot\Delta}{16\alpha-0.95\alpha\Delta}=1+\frac{0.95\alpha+0.1}{16\alpha-0.95\alpha\Delta}\Delta.$$

If the client has not offered profit sharing and the gift was given, DM still chooses X if X is at least weakly better than *Y*. He also chooses *X*, if $\Delta > 0$, if and only if

$$22 + k\cdot\alpha\cdot 16 + \alpha\cdot 0 + l\cdot\alpha\cdot m^C(X) > 22 + k\cdot\alpha\cdot 0 + \alpha\cdot 16 + l\cdot\alpha\cdot(m^C(X) + \Delta)$$
$$\Leftrightarrow \quad k\cdot\alpha\cdot 16 > \alpha\cdot 16 + l\cdot\alpha\cdot\Delta$$
$$\Leftrightarrow \quad k > 1 + l\cdot\frac{\Delta}{16}.$$

Hence, if the gift was given and product *X* is weakly better ($\Delta \le 0$), then DM will always choose *X*. If product *X* is strictly worse ($\Delta > 0$), both inequalities still hold for large enough k, small enough Δ, small enough α, or small enough l. To see that DM is less likely to choose *X* in the IT with profit sharing than in the GT, we compare the thresholds for k:

$$1 + \frac{0.95\alpha + 0.1}{16\alpha - 0.95\alpha\Delta}\Delta > 1 + \frac{\Delta}{16}$$
$$\Leftrightarrow \frac{0.95\alpha + 0.1}{16\alpha - 0.95\alpha\Delta} > \frac{1}{16}$$
$$\Leftrightarrow 0.95\cdot 16\alpha + 1.6 > 16\alpha - 0.95\alpha\Delta$$
$$\Leftrightarrow 1.6 > 0.8\alpha - 0.95\alpha\Delta,$$

which always holds for $\Delta > 0$. Since the threshold in the IT with profit-sharing is strictly larger, DM is less likely to choose *X*.

Similarly, to see that she is more likely to choose *X* in the IT <u>without</u> profit-sharing than in the GT, we compare again thresholds and note that $1 + l\cdot\frac{\Delta}{16} \le 1 + \frac{\Delta}{16}$, with the inequality holding strictly for $l < 1$.

(ii) Suppose now that producer *X* does not pass on the gift. Then DM clearly chooses *Y* in the IT if *Y* is at least weakly better than *X*, no matter whether profit sharing has been offered or not. If *X* is strictly better than *Y* ($\Delta < 0$) and the client offered profit sharing, DM chooses *X* if and only if

$$20 + 0.1\cdot m^C(X) + l\cdot\alpha\cdot 17 + \alpha\cdot 0 + k\cdot\alpha\cdot 0.95\cdot m^C(X)$$
$$> 20 + 0.1\cdot(m^C(X) + \Delta) + l\cdot\alpha\cdot 1 + \alpha\cdot 16 + k\cdot\alpha\cdot 0.95\cdot(m^C(X) + \Delta)$$
$$\Leftrightarrow \quad l\cdot 16\alpha > 0.1\Delta + 16\alpha + k\cdot\alpha\cdot 0.95\Delta$$
$$\Leftrightarrow \quad l > 1 + \frac{0.95\alpha k + 0.1}{16\alpha}\Delta.$$

If $\Delta < 0$ and the client has not offered profit sharing, DM chooses *X* if and only if

$$20 + l\cdot\alpha\cdot 17 + \alpha\cdot 0 + l\cdot\alpha\cdot m^C(X) > 20 + l\cdot\alpha\cdot 1 + \alpha\cdot 16 + l\cdot\alpha\cdot(m^C(X)+\Delta)$$
$$\Leftrightarrow \quad l\cdot 16\alpha > 16\alpha + l\cdot\alpha\cdot\Delta$$
$$\Leftrightarrow \quad l\cdot(16-\Delta) > 16$$
$$\Leftrightarrow \quad l > \frac{16}{16-\Delta}.$$

Hence, if the gift was not given and product *X* is strictly worse ($\Delta > 0$), then DM will never choose *X*. If instead product *X* is strictly better ($\Delta < 0$), both inequalities hold for large enough l, large enough Δ, small enough α, or large enough k, and DM may choose *X*. To see that DM is more likely to choose *X* in the IT with profit-sharing than in the GT, we compare the thresholds for l:

$$1 + \frac{0.95\alpha k + 0.1}{16\alpha}\Delta < 1 + \frac{1}{16}\Delta$$
$$\Leftrightarrow \frac{0.95\alpha k + 0.1}{\alpha} > 1$$
$$\Leftrightarrow 0.95\alpha k + 0.1 > \alpha,$$

which always holds for finite α. Since the threshold in the IT with profit-sharing is strictly smaller, DM is more likely to choose *X*.

Similarly, she is less likely to do so in the IT <u>without</u> profit-sharing than in the GT since, for $\Delta < 0$,

$$\frac{16}{16-\Delta} > \frac{16+\Delta}{16}$$
$$\Leftrightarrow 16^2 > 16^2 - \Delta^2.$$

Q.E.D.

Appendix B: Additional Tables

Appendix-Table A1. Experimental Parameterization

Period	Poten-tial gift giver	Possible payoffs of product *A*		Expected value of *A*	Spread btw. payoffs of *A*	Possible payoffs of product *B*		Expected value of *B*	Spread btw. payoffs of *B*	Diff. in EVs (pot. gift giver minus other)	Diff. in Spreads (pot. gift giver minus other)
		50%	50%			50%	50%				
1	*A*	**13**	**15**	14	2	**20**	**12**	16	8	-2	-6
2	*B*	**15**	**17**	16	2	**12**	**20**	16	8	0	6
3	*B*	**16**	**14**	15	2	**14**	**20**	17	6	2	4
4	*B*	**13**	**19**	16	6	**5**	**15**	10	10	-6	4
5	*A*	**17**	**7**	12	10	**10**	**14**	12	4	0	6
6	*B*	**12**	**16**	14	4	**19**	**13**	16	6	2	2
7	*A*	**11**	**19**	15	8	**18**	**16**	17	2	-2	6
8	*A*	**8**	**20**	14	12	**10**	**18**	14	8	0	4
9	*B*	**17**	**19**	18	2	**10**	**14**	12	4	-6	2
10	*A*	**19**	**13**	16	6	**20**	**8**	14	12	2	-6
11	*B*	**20**	**12**	16	8	**7**	**13**	10	6	-6	-2
12	*B*	**3**	**17**	10	14	**5**	**11**	8	6	-2	-8
13	*A*	**16**	**12**	14	4	**8**	**20**	14	12	0	-8
14	*A*	**9**	**15**	12	6	**19**	**5**	12	14	0	-8
15	*B*	**19**	**11**	15	8	**7**	**19**	13	12	-2	4
16	*A*	**8**	**12**	10	4	**13**	**3**	8	10	2	-6
17	*B*	**20**	**16**	18	4	**16**	**8**	12	8	-6	4
18	*A*	**7**	**13**	10	6	**16**	**8**	12	8	-2	-2
19	*A*	**8**	**14**	11	6	**14**	**12**	13	2	-2	4
20	*B*	**13**	**19**	16	6	**18**	**14**	16	4	0	-2
21	*A*	**2**	**4**	3	2	**18**	**20**	19	2	-16	0
22	*B*	**15**	**17**	16	2	**12**	**20**	16	8	0	6
23	*A*	**2**	**2**	2	0	**17**	**19**	18	2	-16	-2
24	*A*	**19**	**13**	16	6	**20**	**8**	14	12	2	-6
25	*B*	**20**	**18**	19	2	**6**	**0**	3	6	-16	4
26	*B*	**3**	**17**	10	14	**5**	**11**	8	6	-2	-8
27	*A*	**1**	**3**	2	2	**17**	**19**	18	2	-16	0
28	*B*	**12**	**16**	14	4	**19**	**13**	16	6	2	2
29	*B*	**16**	**20**	18	4	**4**	**0**	2	4	-16	0
30	*A*	**2**	**0**	1	2	**15**	**19**	17	4	-16	-2
min		3	7	10	2	5	3	8	2	-6; -16	-8
max		20	20	18	14	20	20	17	14	2	6
avg excl LET		13.20	15.00	14.10	6.00	13.05	13.15	13.10	7.50	-1.40	-0.1
avg incl LET		11.87	13.67	12.77	5.27	13.13	13.07	13.10	6.73	-4.07	-0.27

TABLE A1: Payoffs of the different products in all treatments

In the first 20 periods that we used in all treatments there are

- four periods in which the potential gift giver's expected value is 2 points higher (periods 3, 6, 10, and 16)

- six periods in which there is no difference in expected value between producer *A* and producer *B* (periods 2, 5, 8, 13, 14, and 20)
- six periods in which the potential gift giver's expected value is 2 points lower (periods 1, 7, 12, 15, 18, 19)
- four periods in which the potential gift giver's expected value is 6 points lower (periods 4, 9, 11, 17)

Note that in the four periods in which the potential gift giver's expected value is 6 points lower, his lottery is first order stochastically dominated by the lottery of his competitor.
Note further that there are 10 periods in which the spread between possible payoffs is higher for the product of the potential gift giver than for the alternative product, and 10 periods in which it is lower. Among the six periods with equal expected values, the spread is larger in three periods and lower in the other three periods.

In the Large Externality Treatment (LET) 10 additional periods (periods 21 to 30) are played. In six of those the expected value of the potential gift giver's product is 16 points lower.

Appendix-Table A2. Summary Statistics by Treatment

	Observations					Demographics								
			Type			Gender	Age			Major				
	Total	Subjects	DMs	Producers	Clients	Females	20s	30s	40s-60s	Econ/Business	Humanities	Natur. Scienc.	Other Soc.Sc.	Other
1. **Baseline Treatment (BT)**	480	48	24	0	24	48%	90%	8%	2%	40%	21%	19%	10%	10%
Producers cannot give any gifts														
2. **Gift Treatment (GT)**	960	192	48	96	48	56%	94%	4%	3%	29%	19%	23%	10%	19%
One producer can give a gift														
3. **No Externality Treatment (NET)**	320	48	16	32	0	46%	96%	4%	0%	23%	17%	23%	19%	19%
One producer can give a gift; DM=Client														
No client; DM is residual claimant.														
4. Incentive Treatment (IT)	460	92	23	46	23	55%	96%	4%	0%	28%	15%	16%	11%	29%
One producer can give gift.														
Client can offer profit sharing.														
5. **Large-Gift Treatment (LGT)**	240	48	12	24	12	63%	98%	2%	0%	19%	10%	25%	13%	33%
One producer can give large gift.														
6. **Disclosure Treatment (DCT)**	360	72	18	36	18	50%	93%	4%	3%	15%	21%	25%	17%	22%
One producer can give gift.														
Client informed about gift and DM's response.														
7. Disclosure with Punishment Treatment (DCPT)	360	72	18	36	18	50%	93%	4%	3%	49%	12%	15%	18%	6%
Client informed and can punish														
8. Hiring Treatment (HIRET)	360	72	18	36	18	60%	93%	4%	3%	28%	13%	31%	6%	24%
Client hires DM, increases DM's payoff by 2														
9. Inefficient Gift Treatment (GT2:1)	240	48	12	24	12	69%	83%	15%	2%	31%	10%	21%	6%	31%
Cost of gift is 2, benefit is 1														
10. Welfare Neutral Gift Treatment (GT2:2)	240	48	12	24	12	50%	92%	8%	0%	31%	19%	17%	6%	27%
Cost of gift is 2, benefit is 2														
11. Large Externality Treatment (LET)	120					60%	92%	2%	6%	25%	17%	23%	10%	25%
In some periods externality is 16.														
Additional periods added to two GT sessions.														
Total of reported sessions	**4,140**	**740**	**201**	**354**	**185**	**55%**	**93%**	**5%**	**2%**	**29%**	**16%**	**22%**	**10%**	**23%**

Appendix -Table A3. Gift Treatment (Bootstrapped SES clustered by session)

	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gift given	0.289***	0.290***			0.274***		
	(0.001)	(0.001)			(0.001)		
Gift not given	-0.151***	-0.152***			-0.138***		
	(0.010)	(0.007)			(0.008)		
(Product *X* has same EV)*(Gift given)			0.389***	0.389***		0.391***	0.391***
			(0.001)	(0.001)		(0.000)	(0.000)
(Product *X* has same EV)*(Gift not given)			-0.203***	-0.204***		-0.211***	-0.211***
			(0.006)	(0.006)		(0.006)	(0.006)
(Product *X* has higher EV [+2])*(Gift given)			0.051	0.053		0.043	0.043
			(0.196)	(0.228)		(0.336)	(0.337)
(Product *X* has higher EV [+2])*(Gift not given)			-0.345***	-0.349***		-0.335***	-0.335***
			(0.078)	(0.001)		(0.002)	(0.000)
(Product *X* has lower EV [-2])*(Gift given)			0.366***	0.367***		0.373***	0.373***
			(0.001)	(0.001)		(0.000)	(0.000)
(Product *X* has lower EV [-2])*(Gift not given)			-0.023	-0.024		-0.025	-0.025
			(0.726)	(0.683)		(0.673)	(0.673)
(Product *X* has lower EV [-6])*(Gift given)			0.273***	0.272***		0.272***	0.272***
			(0.007)	(0.010)		(0.012)	(0.008)
(Product *X* has lower EV [-6])*(Gift not given)			-0.0798*	-0.0753*		-0.0752*	-0.0752*
			(0.067)	(0.048)		(0.043)	(0.043)
(Product X has lower EV[-16])*(Gift given)						-	-0.361***
							(0.001)
(Product X has lower EV[-16])*(Gift not given)						0.106	-0.255**
						0.000	(0.348)
Dummies for EV difference of -16						X	
Dummies for all other EV differences			X	X		X	X
Controls for gender, major, and period		X		X	X	X	X
Observations	1440	1440	1'440	1440	1560	1560	1560
(Pseudo) R-squared	0.128	0.131	0.371	0.373	0.119	0.382	0.382
Sample	GT; BT	GT; BT	GT; BT	GT; BT	GT; LET; BT	GT; LET; BT	GT; LET; BT

Notes. The GT, BT, and LET samples contain all data from the Gift, Baseline, and Large Externality Treatment, respectively. The Gift given indicates that producer X sent the gift if it was available. Gift not given indicates that producer X did not send the gift although it was available. P-values estimated using the wild cluster bootstrap t-procedure (clustering by session) are reported. *** denotes significance at 1 percent, ** at 5 percent, and * at 10 percent.

Appendix-Table A4. No Externality Treatment (Bootstrapped SES clustered by session)				
	Diff. to BT	*Diff. to GT*	*Diff. to BT*	*Diff. to GT*
	(1)	(2)	(3)	(4)
NET: Gift given	0.187**	-0.103		
	(0.044)	(0.125)		
NET: Gift not given	-0.068	0.084*		
	(0.382)	(0.059)		
(Product *X* has same EV)*(NET: Gift given)			0.325**	-0.064
			(0.049)	(0.186)
(Product *X* has same EV)*(NET: Gift not given)			-0.080	0.124
			(0.463)	(0.198)
(Product *X* has higher EV [+2])*(NET: Gift given)			0.115	0.062***
			(0.327)	(0.186)
(Product *X* has higher EV [+2])*(NET: Gift not given)			-0.058	0.290***
			(0.476)	(0.097)
(Product *X* has lower EV [-2])*(NET: Gift given)			0.195	-0.171**
			(0.142)	(0.122)
(Product *X* has lower EV [-2])*(NET: Gift not given)			-0.020	0.003
			(0.709)	(0.981)
(Product *X* has lower EV [-6])*(NET: Gift given)			-0.063	-0.335***
			(0.247)	(0.079)
(Product *X* has lower EV [-6])*(NET: Gift not given)			-0.103*	-0.027
			(0.051)	(0.364)
Dummies for (GT: Gift given) and (GT: Gift not given)	X			
Dummies for (Gift given) and (Gift not given)		X		
Dummies for EV differences			X	X
Dummies for EV differences interacted with (GT: gg) and (GT: gng)			X	
Dummies for EV differences interacted with (gg) and (gng)				X
Controls for gender, major, and period	X	X	X	X
Sample	NET, GT, BT	NET, GT, BT	NET, GT, BT	NET, GT, BT
Observations	1'760	1'760	1'760	1'760
R-square	0.123	0.123	0.397	0.397

Notes. The NET sample contains all observations from the No Externality Treatment; the BT sample all observations from the Baseline Treatment; and the GT sample all observations from the Gift Treatment. The abbreviations *gg* and *gng* indicate *Gift given* and *Gift not given* , respectively. Constant included. P-values estimated using the wild cluster bootstrap t-procedure (clustering by session) are reported. *** denotes significance at 1 percent, ** at 5 percent, and * at 10 percent.

Appendix - Table A5. Gift Size and Efficiency of Gift (Bootstrapped SES clustered by session)

	Welfare Neutral Gift (GT2:2)		Inefficient Gift (GT2:1)		Hiring Treatment (HIRET)	
	Diff. to BT	*Diff. to GT*	*Diff. to BT*	*Diff. to GT*	*Diff. to BT*	*Diff. to GT*
	(1)	(2)	(3)	(4)	(5)	(6)
Model 1: Overall Effects						
Respective Treatment: Gift given	0.241**	-0.049	0.216**	-0.074	0.09	-0.199***
	(0.056)	(0.634)	(0.012)	(0.159)	(0.107)	(0.009)
Respective Treatment: Gift not given	-0.102	0.049	-0.076	0.077	-0.139	0.013
	(0.107)	(0.281)	(0.122)	(0.159)	(0.159)	(0.823)
Dummies for (GT: Gift given) and (GT: Gift not given)	X		X		X	
Dummies for (Gift given) and (Gift not given)		X		X		X
Controls for gender, econ major, and period	X	X	X	X	X	X
R-square	0.128	0.128	0.123	0.123	0.120	0.120
Model 2: Estimates by EV differences						
(Product *X* has same EV)*(Treatment: Gift given)	0.291**	-0.098	0.405**	0.016	0.170***	-0.219**
	(0.027)	(0.537)	(0.021)	(0.801)	(0.006)	(0.013)
(Product *X* has same EV)*(Treatment: Gift not given)	-0.222	-0.018	-0.231**	-0.026	-0.183	0.021
	(0.205)	(0.805)	(0.040)	(0.629)	(0.160)	(0.804)
(Product *X* has higher EV [+2])*(Treatment: Gift given)	0.075	0.022	0.072	0.019	0.092	0.040
	(0.241)	(0.643)	(0.156)	(0.625)	(0.214)	(0.234)
(Product *X* has higher EV [+2])*(Treatment: Gift not given)	-0.166	0.182	-0.095	0.255*	-0.298	0.049
	(0.157)	(0.220)	(0.245)	(0.074)	(0.119)	(0.720)
(Product *X* has lower EV [-2])*(Treatment: Gift given)	0.325	-0.042	0.369***	0.003	0.13	-0.237**
	(0.138)	(0.841)	(0.009)	(0.989)	(0.177)	(0.020)
(Product *X* has lower EV [-2])*(Treatment: Gift not given)	-0.068	-0.045	0.046	0.070	-0.034	-0.011
	(0.325)	(0.478)	(0.706)	(0.712)	(0.526)	(0.863)
(Product *X* has lower EV [-6])*(Treatment: Gift given)	0.297	0.024	-0.083*	-0.355**	-0.069	-0.342**
	(0.139)	(0.861)	(0.044)	(0.019)	(0.279)	(0.020)
(Product *X* has lower EV [-6])*(Treatment: Gift not given)	-0.112*	-0.037	-0.116***	-0.040	-0.105*	-0.028
	(0.074)	(0.223)	(0.008)	(0.119)	(0.052)	(0.452)
Dummies for EV differences	X	X	X	X	X	X
Dummies for EV differences interacted with (GT: gg) and (GT: gng)	X		X		X	
Dummies for EV differences interacted with (gg) and (gng)		X		X		X
Controls for gender, major, and period	X	X	X	X	X	X
R-square	0.366	0.366	0.392	0.392	0.386	0.386
Sample	GT2:2, GT, BT	GT2:2, GT, BT	GT2:1, GT, BT	GT2:1, GT, BT	HIRET; GT; BT	HIRET; GT; BT
Observations	1'680	1'680	1'680	1'680	1'800	1'800

Notes . The HIRET sample contains all observations from the Hiring Treatment, GT2:1 and GT2:2 sample the observations from the Gift Treatments with efficiency 2:1 and 2:2, respectively; BT the observations from the Baseline Treatment; and GT the observations from the Gift Treatment. The abbreviations gg and gng indicate "gift available and given" and "gift available but not given," respectively. Constant included. P-values estimated using the wild cluster bootstrap t-procedure (clustering by session) are reported. *** denotes significance at 1 percent, ** at 5 percent, and * at 10 percent.

Appendix - Table A6. Policy Treatments (Bootstrapped SES clustered by session)

	Disclosure (DCT)		Disclosure w. Punishm. (DCPT)			Large Gift (LGT)		Incentive-ps (IT-ps)		Incentive-nps (IT-nps)	
	Diff. to BT	*Diff. to GT*	*Diff. to BT*	*Diff. to GT*	*Diff. to DCT*	*Diff. to BT*	*Diff. to GT*	*Diff. to BT*	*Diff. to GT*	*Diff. to BT*	*Diff. to GT*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Model 1: Overall Effects											
Respective Treatment: Gift given	0.223***	-0.066	0.212**	-0.077	-0.011	0.159*	-0.130*	0.246**	-0.044	0.388***	0.098***
	(0.010)	(0.272)	(0.037)	(0.321)	(0.880)	(0.076)	(0.099)	(0.018)	(0.688)	(0.019)	(0.089)
Respective Treatment: Gift not given	-0.109	0.045	-0.087*	0.065*	0.019	-0.071	0.083	-0.052	0.100	-0.120**	0.031
	(0.090)	(0.360)	(0.079)	(0.056)	(0.620)	(0.905)	(0.197)	(0.992)	(0.362)	(0.104)	(0.540)
Dummies for (GT: Gift given) and (GT: Gift not given)	X		X		X	X		X		X	
Dummies for (Gift given) and (Gift not given)		X		X	X		X		X		X
Controls for gender, econ major, and period	X	X	X	X	X	X	X	X	X	X	X
R-square	0.123	0.123	0.12	0.12	0.115	0.116	0.116	0.128	0.128	0.156	0.156
Model 2: Estimates by EV differences											
(Product *X* has same EV)*(Treatment: Gift given)	0.309**	-0.080	0.289***	-0.100	-0.020	0.297*	-0.092	0.393***	0.004	0.371**	-0.019
	(0.016)	(0.146)	(0.004)	(0.143)	(0.747)	(0.085)	(0.170)	(0.009)	(0.953)	(0.028)	(0.886)
(Product *X* has same EV)*(Treatment: Gift not given)	-0.063	0.142	-0.191*	0.013	-0.130	-0.209	-0.003	-0.199	0.005	-0.191*	0.011
	(0.273)	(0.084)	(0.070)	(0.700)	(0.650)	(0.670)	(0.967)	(0.540)	(0.960)	(0.100)	(0.881)
(Product *X* has higher EV [+2])*(Treatment: Gift given)	0.102**	0.05	0.072	0.02	-0.029	-0.037	-0.090	0.063	0.010	0.069	0.016
	(0.037)	(0.135)	(0.269)	(0.639)	(0.590)	(0.517)	(0.115)	(0.230)	(0.826)	(0.137)	(0.676)
(Product *X* has higher EV [+2])*(Treatment: Gift not given)	-0.191	0.158	-0.099	0.25	0.089	-0.155	0.197	-0.003	0.346**	-0.733***	-0.387**
	(0.091)	(0.330)	(0.368)	(0.159)	(0.538)	(0.668)	(0.419)	(0.975)	(0.048)	(0.009)	(0.035)
(Product *X* has lower EV [-2])*(Treatment: Gift given)	0.289**	-0.078	0.295*	-0.072	0.006	0.199*	-0.167*	0.223	-0.144	0.505***	0.137**
	(0.010)	(0.405)	(0.098)	(0.662)	(0.958)	(0.077)	(0.096)	(0.164)	(0.067)	(0.005)	(0.049)
(Product *X* has lower EV [-2])*(Treatment: Gift not given)	-0.074	-0.049	-0.068	-0.044	0.004	0.199	0.224	0.102	0.126	0.088	0.110
	(0.198)	(0.337)	(0.460)	(0.541)	(0.939)	(0.170)	(0.464)	(0.471)	(0.270)	(0.454)	(0.210)
(Product *X* has lower EV [-6])*(Treatment: Gift given)	0.07***	-0.202	0.157	-0.116	0.086	0.108	-0.163	0.015	-0.258	0.564**	0.290**
	(0.428)	(0.056)	(0.159)	(0.252)	(0.431)	(0.049)	(0.143)	(0.958)	(0.178)	(0.011)	(0.018)
(Product *X* has lower EV [-6])*(Treatment: Gift not given)	-0.065	0.012	-0.107*	-0.032	-0.044	-0.132	-0.056	-0.099	-0.023	0.270**	0.345***
	(0.270)	(0.819)	(0.074)	(0.216)	(0.337)	(0.350)	(0.427)	(0.349)	(0.379)	(0.024)	(0.001)
Dummies for EV differences	X	X	X	X	X	X	X	X	X	X	X
Dummies for EV differences interacted with (GT: gg) and (GT: gng)	X		X		X	X		X		X	
.Dummies for EV differences interacted with (gg) and (gng)		X		X	X		X		X		X
Controls for gender, major, and period	X	X	X	X	X	X	X	X	X	X	X
R-square	0.38	0.38	0.369	0.369	0.376	0.363	0.363	0.381	0.381	0.361	0.361
Sample	DCT, GT, BT	DCT, GT, BT	DCPT, GT, BT	DCPT, GT, BT	:PT; DCT; GT;	LGT, GT, BT	LGT, GT, BT	IT-ps; GT; BT	IT-ps; GT; BT	IT-nps; GT; BT	IT-nps; GT; BT
Observations	1'800	1'800	1'800	1'800	2,160	1'680	1'680	1'571	1'571	1'769	1'769

Notes. The DCT, DCPT, and LGT samples contain all data from the Disclosure, Disclosure with Punishment, and Large Gift Treatment, respectively. The data from the Incentive Treatment are split into IT-ps (when the client offered profit sharing) and IT-nps (when the client did not offer profit sharing). BT contains the observations from the Baseline Treatment; and GT the observations from the Gift Treatment. The abbreviations gg and gng indicate "gift available and given" and "gift available but not given," respectively. Constant included. P-values estimated using the wild cluster bootstrap t-procedure (clustering by session) are reported. *** denotes significance at 1 percent, ** at 5 percent, and * at 10 percent.

Appendix - Table A7. Additional Treatments

	DCPT-PI			ICT		SIT	
	Diff. to BT	*Diff. to GT*	*Diff. to DCPT*	*Diff. to BT*	*Diff. to GT*	*Diff. to BT*	*Diff. to GT*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model 1: Overall Effects							
Respective Treatment: Gift given	0.381***	0.091**	0.169***	0.105**	-0.185***	0.244***	-0.046
	(0.041)	(0.039)	(0.046)	(0.047)	(0.046)	(0.042)	(0.040)
Respective Treatment: Gift not given	-0.105**	0.047	-0.018	-0.131***	0.022	0.032	0.185***
	(0.053)	(0.054)	(0.067)	(0.049)	(0.051)	(0.068)	(0.069)
Dummies for (GT: Gift given) and (GT: Gift not given)	X		X	X		X	
Dummies for (Gift given) and (Gift not given)		X	X		X		X
Controls for gender, econ major, and period	X	X	X	X	X	X	X
R-square	0.148	0.148	0.135			0.122	
Model 2: Estimates by EV differences							
(Product *X* has same EV)*(Treatment: Gift given)	0.465***	0.075	0.175***	0.217***	-0.172**	0.389***	-0.000
	(0.060)	(0.051)	(0.067)	(0.080)	(0.074)	(0.065)	(0.057)
(Product *X* has same EV)*(Treatment: Gift not given)	-0.245***	-0.041	-0.053	-0.206**	-0.002	-0.075	0.130
	(0.091)	(0.093)	(0.116)	(0.096)	(0.099)	(0.129)	(0.131)
(Product *X* has higher EV [+2])*(Treatment: Gift given)	0.117***	0.064***	0.046	0.083*	0.030	-0.008	-0.061
	(0.033)	(0.022)	(0.029)	(0.045)	(0.037)	(0.066)	(0.061)
(Product *X* has higher EV [+2])*(Treatment: Gift not given)	-0.195	0.155	-0.098	0.032	0.381***	-0.016	0.335***
	(0.123)	(0.138)	(0.147)	(0.073)	(0.096)	(0.098)	(0.116)
(Product *X* has lower EV [-2])*(Treatment: Gift given)	0.495***	0.128*	0.200**	-0.008	-0.374***	0.300***	-0.067
	(0.072)	(0.076)	(0.087)	(0.054)	(0.059)	(0.068)	(0.072)
(Product *X* has lower EV [-2])*(Treatment: Gift not given)	0.047	0.071	0.116	-0.085**	-0.061	0.064	0.088
	(0.085)	(0.086)	(0.091)	(0.042)	(0.044)	(0.103)	(0.103)
(Product *X* has lower EV [-6])*(Treatment: Gift given)	0.325***	0.053	0.169	-0.031	-0.303***	0.165**	-0.106
	(0.101)	(0.104)	(0.113)	(0.064)	(0.068)	(0.084)	(0.087)
(Product *X* has lower EV [-6])*(Treatment: Gift not given)	-0.015	0.059	0.093	-0.066	0.010	0.104	0.177*
	(0.069)	(0.066)	(0.062)	(0.053)	(0.050)	(0.105)	(0.103)
Dummies for EV differences	X	X	X	X	X	X	X
Dummies for EV differences interacted with (GT: gg) and (GT: gng)	X		X	X		X	
.Dummies for EV differences interacted with (gg) and (gng)		X	X		X		X
Controls for gender, major, and period	X	X	X	X	X	X	X
R-square	0.381	0.381	0.376	0.402	0.402	0.367	0.367
Sample	DCPT-PI, GT, BT	DCPT-PI, GT, BT	DCPT; DCPT-PI; GT; BT	ICT; GT; BT	ICT; GT; BT	SIT; GT; BT	SIT; GT; BT
Observations	1'680	1'680	2,040	1,680	1,680	1,680	1,680

Notes . The DCPT and DCPT-PI samples contain the observations from the Disclosure With Punishment Treatment, and the Disclosure With Punishment And Partial Information Treatment, respectively. The BT and GT samples contain the observations from the Baseline Treatment, and the Gift Treatment, respectively. The SIT and ICT samples contain the observations from the Small Incentive Treatment and the "ICT"-Incentive Treatment, respectively. The abbreviations gg and gng indicate "gift available and given" and "gift available but not given," respectively. Constant included. Robust standard errors are reported. *** denotes significance at 1 percent, ** at 5 percent, and * at 10 percent.

Appendix C: The Wild Cluster Bootstrap-T

A common concern in the analysis of experimental data is the possibility that observations may be correlated within session, due to day effects, (time-varying) experimenter effects, or other unobserved factors. One way to address this concern is to allow the error term to be clustered by session. However, in our experiment setting, we have only 31 sessions. Standard asymptotic tests tend to over-reject if the number of clusters (i.e., sessions) is small. We implement the wild cluster bootstrap-t procedure, first proposed by Cameron, Gelbach, and Miller (2008) to correct standard errors in estimations with few clusters. We cluster by both session and subject.

The general bootstrap method, as introduced by B. Efron (1979), works by generating pseudo-samples from an original sample and calculating a statistic of interest within each pseudo-sample, and then using the distribution of the statistic of interest to infer the distribution of the original sample statistic.

There are many ways to generate pseudo-samples and therefore there exists a wide variety of bootstrap methods. In order for a bootstrap method to be applicable, the resampling method chosen should reflect the original data generating process (DGP) as closely as possible. Wu (1986) first suggested using a bootstrap method known as the wild bootstrap in order to deal with cases with heteroskedastic errors. Liu (1988) and Mammen (1993) provide theoretical justification for using the wild bootstrap in cases with heteroskedastic errors. Cameron, Miller, and Gelbach (2008) extend the wild bootstrap procedure to cases with clusters. They show that their wild cluster bootstrap-t procedure works well even with few clusters (as few as 5). Their basic argument for using certain bootstrap methods over others when the number of clusters is small is as follows. They propose that the key in these cases is to bootstrap an asymptotically pivotal statistic, meaning a statistic whose asymptotic distribution does not rely on unknown parameters. This leads to asymptotic refinement, i.e., the distribution of the test statistic converges faster to the true distribution than test statistics based on conventional asymptotic theory.

Cameron, Miller, and Gelbach (2008) suggest the asymptotically pivotal Wald statistic $w = \frac{\widehat{\beta_1} - \beta_1^0}{s_{\widehat{\beta_1}}}$ where $s_{\widehat{\beta_1}}$ is the standard error of $\widehat{\beta_1}$ and $H_o\colon \beta_1 = \beta_1^0$and $H_a\colon \beta_1 \neq \beta_1^0$. Theoretically, we may use a variety of bootstrap methods in order to provide bootstrap estimates of the Wald statistic. Cameron, Miller, and Gelbach (2008) find that the wild cluster bootstrap-t procedure performs particularly well in practice.

Below, we show the wild cluster bootstrap-t procedure implemented to bootstrap the Wald statistic for the coefficient on giving a gift. We are comparing behavior in the *Gift Treatment* and in the *Baseline Treatment*. The procedures for different treatments and for the Wald statistic when the gift was not given are completely analogous.

1. In original sample, estimate the model

$$Y_i = \beta_0 + \beta_{gift} * GiftGiven_i + \beta_{Nogift} * GiftNotGiven_i + u_i$$

   Form Wald statistic for $H_o: \beta_{gift} = 0$

$$w = \frac{\widehat{\beta_{gift}}}{s_{\widehat{\beta_{gift}}}}$$

   where $s_{\widehat{\beta_{gift}}}$is obtained using the cluster-robust variance estimator. In STATA this is obtained using the cluster option.

2. Estimate the restricted model $Y_i = \beta_0 + u_i$. Obtain the restricted model $\widehat{\beta_0}^R$ and the associated residuals $\{\widehat{u_1{}^R}, \dots , \widehat{u_G{}^R}\}$ where $\widehat{u_g}^R$is the vector of residuals obtained from cluster g. Note that existing literature on bootstrap methods advocate the use of bootstrap resampling methods that impose the null hypothesis. Therefore, in all of the reported results, we use a bootstrap method which imposes the null hypothesis. Also, had we included demographic controls as regressors (which we do in other cases) our restricted model would have included terms for these controls. We restrict only the coefficients of interest (gift given and gift not given). One may perform the restricted OLS estimation by restricting both coefficients on the statistics of interest simultaneously, or each individually. We perform both procedures.

3. Do *B* iterations of the next step. On the b^{th}iteration:
   a. form a pseudo sample of *G* clusters $(\widehat{Y_1^*}, X_1), \dots , (\widehat{Y_G^*}, X_G)$ by the following method: For each cluster g = 1,…,*G*, form either $\widehat{u_g^{R_*}}$=$\widehat{a_g u_g{}^R}$, where $a_g = 1$ with probability 0.5 and $a_g = -1$with probability 0.5. Note that when using weights of this form, the maximum possible unique resamples is equal to 2^G. In many cases we have as few as five clusters, resulting in 32 unique resamples. Webb (2012) argues that inference can be improved by adding points to the weighting distribution. He proposes a six-point

weighting distribution and provides Monte Carlo evidence to support using such a distribution. When we implement the wild cluster bootstrap-t procedure using a six-point weighting distribution, the results did not change significantly.

b. Form $\widehat{Y_g^*} = \widehat{\beta_0}^R + \widehat{u_g^{R*}}$. If other regressors such as demographic controls were included then the bootstrap sample would be formed by also adding the additional regressors multiplied by the estimates of their coefficients in the restricted regression.

c. Calculate the Wald test statistic $w_b^* = \frac{\widehat{\beta_{gift,b}}^R}{s_{\widehat{\beta_{gift,b}^*}}}$, where $\widehat{\beta_{gift,b}}^R$ and its standard error $s_{\widehat{\beta_{gift,b}^*}}$ are obtained from the unrestricted OLS estimation using the b^{th} pseudo-sample, with $s_{\widehat{\beta_{gift,b}^*}}$ calculated using cluster-robust standard errors.

4. The *p*-value is calculated by:

$$p^*(w) = 2 * \min\left(\frac{1}{B}\sum_{b=1}^{B} I(w_b^* > w), \frac{1}{B}\sum_{b=1}^{B} I(w_b^* \leq w)\right)$$

where $I(.)$ is the indicator function.

As an illustrative example, we will present a discussion of the original wild bootstrap procedure, taken from Liu (1988). The following displays how the wild bootstrap can be used for accurate estimation in cases with heteroskedasticity. This original wild bootstrap does not take into account clustering, but the extension to clusters does not greatly alter the procedure. Therefore, going through the relatively simple example of Liu (1988) allows for a better understanding of why the procedure developed in Cameron, Miller, and Gelbach (2008) provides consistent estimates of the Wald statistic when allowing for clustered errors. Liu (1988) focuses on a simple regression of the form $Y_i = \beta x_i + \varepsilon_i$, where $x_i's$ are nonzero real numbers, $E(\varepsilon_i) = 0$, $Var(e_i) = \sigma_i^2$, and e_i's are independent. The least squares estimate of β is $\hat{\beta} = \frac{\sum_{i=1}^n x_i Y_i}{\sum_{j=1}^n x_j^2}$. Therefore, in this simple case with one regressor and no constant, $Var(\hat{\beta}) = \frac{n^{-1}\sum_{i=1}^n x_i^2 \sigma_i^2}{(\sum_{j=1}^n x_j^2)^2}$. Let $u_i = Y_i - x_i\hat{\beta}$ be the residuals. If one employed a traditional residual bootstrap, then the bootstrap sample would be $Y_i^* = x_i\hat{\beta} + u_i^*$ where $u_1^*, \ldots, u_n^*$ is a random sample drawn from the empirical d.f based on $(u_1 - \overline{u_n}), \ldots, (u_n - \overline{u_n})$. Let $\widehat{\beta_b}$ denote the least squares estimate based on the bootstrap sample. Then the bootstrap variance is $Var(\widehat{\beta_b}) = \frac{n^{-1}\sum_{i=1}^n (u_1 - \overline{u_n})^2}{(\sum_{j=1}^n x_j^2)^2}$ which is equivalent to

$\frac{n^{-1}\sum_{i=1}^{n}\sigma_i^2}{(\sum_{j=1}^{n}x_j^2)^2}$ asymptotically. Therefore, this bootstrap procedure does not result in a consistent estimate of the standard error of $\hat{\beta}$ if the error variances are allowed to vary. It is easy to alter the bootstrap procedure in order to achieve a consistent estimate. Instead of drawing a bootstrap sample of residuals from the empirical d.f based on $\{(u_i - \overline{u_n})\}$, draw the bootstrap from the empirical distribution based on $\{(x_i/\overline{(x_n^2)}^{\frac{1}{2}}(u_i - \overline{u_n})\}$, where $\overline{(x_n^2)} = \frac{1}{2}\sum_{i=1}^{n}x_i^2$ and let $\widetilde{\beta_b}$ denote the resulting bootstrap least squares estimator of $\hat{\beta}$. Now,

$$Var(\widetilde{\beta_b}) = \frac{\sum_{i=1}^{n}x_i^2u_i^2}{(\sum_{j=1}^{n}x_j^2)^2} - \frac{n^{-1}\sum_{i=1}^{n}(x_iu_i)^2}{(\sum_{j=1}^{n}x_j^2)^2}$$

Which is asymptotically equal to

$$\frac{\sum_{i=1}^{n}x_i^2\sigma_i^2}{(\sum_{j=1}^{n}x_j^2)^2} + O_p(n^{-\frac{3}{2}})$$

So when we draw our bootstrap residuals from the empirical d.f. described above, we get a consistent estimate of the standard error for $\hat{\beta}$.

In order to implement a bootstrap procedure which results in drawing from the desired empirical d.f, Liu (1988) asserts that the bootstrap sample should be

$$Y_1^*, \ldots, Y_n^* \text{ where } Y_i^* = x_i\hat{\beta} + t_iu_i \text{ with } E(t_i) = 0 \text{ and } Var(t_i) = 1.$$

There are many options for t_i. Davidson and Flachaire (2001) provide theoretical justification and Monte Carlo evidence favoring Rademacher weights. Rademacher weights are such that $t_i = 1$ with $p = \frac{1}{2}$ and $t_i = -1$ with $p = \frac{1}{2}$. In all of our reported bootstrap results, we use the Rademacher weights. However, in unreported results, we implemented the bootstrap procedure using the six-point distribution suggested in Webb (2012). The results are similar. Davidson and Flachaire (2001) provide justification for using the residuals and coefficients from a restricted OLS estimation, and therefore the bootstrap sample in the procedure defined above is

$$\widehat{Y_g^*} = \widehat{\beta_0}^R + \widehat{u_g^{R*}}.$$

References for Appendix C

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