Spillovers of Prosocial Motivation: Evidence from an Intervention Study on Blood Donors

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Abstract

Blood donations are increasingly important for medical procedures, while meeting demand is challenging. This paper studies the role of spillovers arising from social interactions in the context of voluntary blood donations. We analyze a large-scale intervention among pairs of blood donors who live at the same street address. A quasi-random phone call provides the instrument for identifying the extent to which the propensity to donate spills over within these pairs. Spillovers transmit 41% to 46% of the behavioral impulse from one donor to the peer. This creates a significant social multiplier, ranging between 1.7 and 1.85. There is no evidence that these spillovers lead to intertemporal substitution. Taken together, our findings indicate that policy interventions have a substantially larger effect when targeted towards pairs instead of isolated individuals.

Keywords: Voluntary Blood Donation, Social Interaction, Bivariate Probit

JEL Classification: D90, C36, C93

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1 Introduction

Blood donations are increasingly important for medical procedures (World Health Organization 2011; Slonim, Wang and Garbarino 2014). However, concerns have been raised that the future demand for blood transfusion may not be met, mainly due to the ageing of the general population (Currie et al. 2004; Ali, Auvinen and Rautonen 2010; Volken et al. 2018). Blood bank's shortages often delay certain surgeries, which can increase the costs to the healthcare system later on (Erickson et al. 2008). Even predictable (e.g. seasonal) shortages can affect routine care of clinic patients and a variety of inpatient needs (Beliën and Forcé 2012). Paying directly for blood donations is generally not considered as a viable means for increasing turnout and is strongly opposed by the World Health Organization (2010). Therefore, blood transfusion services largely rely on voluntary donations. This invites the question of how voluntary blood donors can be motivated to increase turnout.[1]

This paper studies spillovers in the propensity to donate within pairs of blood donors who share the same address. In particular, we explore the extent to which such spillovers are driven by motivational complementarities. Similar to the Battle of the Sexes game, motivational complementarities within these pairs of donors could emerge from various mechanisms, such as enjoyment of shared experiences, cost reductions due to shared transportation, image motivation, or peer pressure. Each of these mechanisms shares the feature that the (net) benefit from donating increases for the focal donor if the peer donates. As we show in an analytical example in the Appendix, this creates a motivational complementarity: if one donor becomes more motivated to donate, this also makes the peer more likely to donate. This, in turn, affects the focal donor again, producing a "social multiplier", akin to a Keynesian consumption multiplier that amplifies the effect of the original intervention.

We use data from the Blood Transfusion Service of the Red Cross in Zurich, Switzerland (BTSRC) on donors who are pre-registered in the same blood drives. This allows us to analyse social interactions among pairs of donors who live at the same street address and are likely to exhibit strong social ties.[2] Our sample consists of 5,053 pairs of donors

[1]Several studies examine the impacts of offering cash-like incentives such as gift cards (Ferrari et al. 1985; Lacetera, Macis and Slonim 2012a; Niessen-Ruenzi, Weber and Becker 2014), or other material incentives like t-shirts (Reich et al. 2006) or health tests (Goette et al. 2009). They find that, in general, offering material incentives increases blood donations. Other interventions, such as pointing out the scarcity of a certain blood type in a personal phone call (Bruhin et al. 2015) or through text messages (Sun, Lu and Jin 2016), as well as highlighting the emphatic motive in a personal phone call (Reich et al. 2006) are also highly effective. See Goette, Stutzer and Frey (2010) or Lacetera, Macis and Slonim (2013) for a more extensive review.

[2]Note that the address only allows us to determine whether the individuals live in the same building with a given house number, but not whether they actually live in the same flat or different flats within the same apartment building. Thus, our sample may consist of a large proportion of couples and the magnitude and nature of spillovers may differ substantially from those arising between people who are more remotely connected.

who were repeatedly invited to blood drives over the sample period from April 2011 to January 2013, leading to 13,421 pair-observations. All donors received a personalized invitation letter several weeks ahead of the upcoming blood drive and a text message reminder on her cell phone a day before the event.

Identifying spillovers in the propensity to donate within these pairs of donors is difficult, as simply observing a correlation in behavior within them is not necessarily evidence of such spillovers (Manski 2000; Durlauf 2002; Graham 2016). First of all, pairs are endogenously formed. Thus, both donors may share similar characteristics and can be exposed to similar environments affecting their propensity to donate. Furthermore, the presence of spillovers itself creates an endogeneity problem known as the reflection problem (Manski 1993), as motivational complementarities feed back and forth between the donors.

In order to overcome these challenges, we use a randomized phone call as an instrument. The phone call targets a random subset of donors whose blood type is currently in short supply. All these donors were previously invited to blood drives through the invitation letters and text messages. The phone call reaches them two days before the upcoming blood drive and encourages them to donate by explaining that their blood type is currently in short supply.

The phone call satisfies two properties that make it a valid instrument. First, it directly increases the recipient's propensity to donate (Bruhin et al. 2015). As the phone call is randomized conditional on blood types, it is exogenous to the recipient's baseline propensity to donate and her other characteristics. In addition, it leaves the peer's propensity to donate and characteristics unaffected, unless the donors within the pair interact. It is important to note that the phone call takes place after the invitation letter and before the text message. Thus, it only explicitly conveys the additional information about the scarcity of the particular recipient's blood type.

To estimate the spillovers in the propensity to donate, we apply a linear-in-means model (Manski 1993; Graham and Hahn 2005) in a bivariate probit specification.[3] The empirical model allows us to distinguish the spillovers arising from endogenous social interactions within the pairs from exogenous social interactions and potential correlations in unobservable characteristics that may also affect donations.

We find strong evidence for spillovers in the propensity to donate within the pairs of donors. Calling up the donor raises her propensity to donate by roughly 11 percentage points (over a baseline of roughly 30 percentage points). The phone call also raises her peer's propensity to donate by 5 percentage points. These findings imply that 46% of the motivational impulse spills over to the peer. The finding is robust across different specifications.

[3]We also present a simple theoretical model to illustrate how spillovers can increase blood donations and how it is mapped to our empirical setup in Section A.1 in the Appendix.

In the context of voluntary blood donations, Lacetera, Macis and Slonim (2014) provide compelling evidence of social interactions taking place among donors. In their setting, they announce to a subset of blood donors that they will be given a stored-value card if they donate blood. Interestingly, they find that a treatment effect also percolates to other donors who were not made aware of the incentives, pointing to the transmission of information about these incentives as the driver of the social interactions.[4] In our setting, however, there is no such information about incentives that can be transmitted. The phone call only conveys information about the scarcity of recipient-specific blood types among otherwise equally well-informed donors.

Our setting allows us to test whether the phone call perhaps also transmits information about i) the scarcity of a particular blood type, or ii) the blood drive per se, within pairs. First, we examine whether a phone call to a focal donor also affects the peer's propensity to donate if they have incompatible blood types. If it were exclusively the information about the temporary shortage of a specific blood type that is transmitted, the effect should be absent for a peer with an incompatible blood type, or at least significantly weaker: if the peer's blood type is incompatible with the one in short supply, donating her blood does not help to reduce that particular shortage. Therefore, she should not react to the information of the phone call as strongly as a peer with a compatible blood type. However, we find the same effect as the peers with compatible blood types.[5] Second, we check whether a phone call to a peer simply serves as a reminder of the blood drive. In this case, the peer's phone call should have less of an effect on the focal donor if the focal donor received a phone call as well. But we find no evidence thereof.

In addition to the testable predictions regarding the peer's behavior, our model also predicts that the focal donor's response to a phone call is amplified by motivational complementarities. Our estimates imply that, in the absence of a peer, the phone call would only raise donations by 7.8 percentage points, instead of the 11 percentage points we observe in our sample. This lower estimate of the effectiveness on an "isolated" donor matches exactly the estimates in Bruhin et al. (2015) on a sample of mostly unconnected donors. Thus, motivational complementarities can account for, both, the impact of the phone call on a peer, and the amplification of the focal donor's response to the phone call.

Spillovers emerging from motivational complementarities lead to a social multiplier that alters the cost-benefit calculations of policy interventions. The estimates of our baseline specification indicate that 46 percent of the initial impulse from the phone call spills over to the peer. In turn, 46 percent of that increase in the peer's motivation

[4] Lacetera, Macis and Slonim (2014) write "Informing individuals of rewards through official ARC channels led others who were not officially informed of the rewards (including active, lapsed, and new donors) to be more likely to donate." (p. 1108)

[5] This test yields the same result if we use the *same* blood types, instead of *compatible* blood types, as, arguably, not all donors are aware of the compatibility between blood types.

spills back to the focal donor, and so on. The resulting feedback loop amplifies the effect of the phone call by $1/(1-0.46^2)$ for the focal donor, and by $0.46/(1-0.46^2)$ for the peer. Overall, the resulting social multiplier is the sum of the two, and corresponds to $1/(1-0.46) = 1.85$. Even in our strictest specification, we find that 41 percent of the propensity to donate spills over to the peer, yielding a lower-bound multiplier of $1/(1-0.41) = 1.7$. Thus, spillovers emerging from motivational complementarities raise the effectiveness of policy interventions by 70 to 85 percent. This demonstrates that behavioral interventions have a substantially larger effect when targeted towards pairs instead of isolated donors.[6] Moreover, there is no evidence that these spillovers lead to intertemporal substitution. Donors whose peers were called up at the last blood drive do not show any tendency to reduce blood donations in the current drive.

Taking into account the spillovers arising from motivational complementarities is particularly important in the context of voluntary blood donations, where more is not always better. Blood products have a limited shelf life (42-49 days for red blood cells in our sample) and disposal is costly (Garbarino et al. 2017). Hence, accounting for such spillovers should allow blood transfusion services to better align supply with demand.

Apart from the literature on blood donation cited earlier, our study also contributes to the broader literature on identifying endogenous social interaction and highlights the importance of social multipliers in various contexts. For example, Cipollone and Rosolia (2007) find strong social interactions within high schools, where an increment in the boys' graduation rate leads to an increase in the girls' graduation rate. Similarly, Lalive and Cattaneo (2009) conclude that when a child stays longer in school, his friends stay longer too. Borjas and Doran (2015) discover strong knowledge spillovers in collaboration spaces when high-quality researchers directly engage with other researchers in the joint production of new knowledge. Finally, Kessler (2013) shows in an experimental study that subjects making non-binding announcements of their contributions to a public good motivate other subjects to contribute as well.

The paper is organized as follows. Section 2 describes the empirical set-up. Section 3 presents our econometric analysis. Section 4 discusses the results and some extensions. Section 5 concludes.

2 The Empirical Setup

This section explains the origin and structure of the panel data set, how we isolate pairs of donors with potential social interactions, and the phone call we use as the instrument

[6] We also explore the role of the nonlinearity in the bivariate probit model by re-estimating our model by two-stage least squares (TSLS). Although the models differ slightly in their interpretations, we also find significant spillover effects in the TSLS specification, and virtually the same implied social multiplier. The results can be found in Section A.2 in the Appendix.

for identifying spillovers in the propensity to donate.

2.1 Origin and Structure of the Data

Our data comprises donors with blood types A-, A+, O-, and O+ who are registered in the BTSRC's database because they donated at least once prior to our study. Since their blood types are in high demand, the BTSRC invites them regularly to blood drives.[7]

The BTSRC uses the following invitation procedure. For each upcoming blood drive, it sends a personalized invitation letter to all eligible donors in its database, i.e. those who did not donate within the past three months and meet all other donation criteria. The letters are mailed several weeks ahead of the blood drive. In addition, all invited donors receive a text message one day ahead of the blood drive, reminding them of the upcoming event. Over the study period from April 2011 to January 2013, each registered donor received between 1 to 8 such invitations.

The invitations constitute the unit of observation in our panel data set. For each of them, we observe: a binary indicator on whether the donor made a donation at the blood drive she was invited to, her street (in acronymized form), house number, and zip code, as well as her age, gender, blood type, and the number of donations she made in the year prior to the study. Moreover, we also observe whether the donor additionally received a phone call, informing her that her blood type is currently in short supply. Panel A of Table 1 shows that the raw data set contains 121,586 such observations stemming from 39,417 donors. The average age of all donors is 43.4 years, and 56.2 percent of them are male. On average, these donors made 0.312 donation per invitation and 0.893 donations in the year before our study.

2.2 Pairs of Donors

To test for spillovers in the propensity to donate, we isolate pairs of donors who share the same street address. They live either as couples or as flat mates in the same dwelling or as neighbors in the same apartment building. There are two advantages of focusing on pairs of donors. First, by eliminating groups of donors who live in large, anonymous apartment buildings, it maximizes the chance that the two donors know each other and exhibit strong social ties. Second, it allows us to apply a bivariate probit model which is often used for estimating the effect of an endogenous binary regressor on a binary outcome variable (Abadie 2000; Angrist 2001; Winkelmann 2012).

Panel B of Table 1 shows that the data set contains 13,421 observations from 5,053 such pairs of donors. The descriptive statistics of the donors in these pairs are similar to

[7]Blood drives are regular events that typically take place twice a year at which donations can be made. They are coordinated by local organizations such as church chapters or sports clubs, but organized centrally by the BTSRC which administers the invitation of donors and provides the equipment and personnel to draw blood.

Table 1: Descriptive statistics of donations

Panel A: Universe of donors

Variable	Mean	Std. Dev.
Donation per invitation	0.312	0.464
Age	43.402	13.365
Male	0.562	0.496
Donations in year before study	0.893	0.832
# of individual donors	39,417	
# of individual observations	121,586	

Panel B: Pairs of donors

Variable	Mean	Std. Dev.
Donation per invitation	0.325	0.468
Age	42.457	13.093
Male	0.521	0.500
Donations in year before study	0.919	0.825
# of pairs	5,053	
# of pair-observations	13,421	
# of individual observations	26,842	

those of all donors in the sample: on average, 32.5% of the invitations led to a donation, the donors are 42.457 years old, 52.1% of them are male, and they made 0.919 donations in the year prior to the study. About 74 percent of the pairs are opposite-gender. This suggests that couples make up a significant proportion of our sample.[8]

Table 2 shows the correlation of donation decisions within pairs of donors. Panel A shows that given that the peer donates, in about 54 percent of the cases the focal donor donates as well. If the peer does not donate, the focal donor donates only in 22 percent of the cases. Panel B illustrates this correlation from a different angle, i.e., by looking at the joint distribution of donations within pairs: 17.5% of all pair-observations exhibit two

[8] One may suspect that most of the spillovers we identify in this study originate from the couples in our data set, who arguably have much stronger social ties than the other cohabiting tenants. This would result in latent behavioral heterogeneity as the group of couples would exhibit stronger spillovers than the group of cohabiting tenants. However, we find no evidence for such latent behavioral heterogeneity. A finite mixture model fails to uncover any groups of donors that differ in the strength of their spillovers (see Appendix A.3 for further details). Thus, the couples and the other cohabiting tenants exhibit spillovers of similar strength, and our results are not purely driven by the couples. This may be explained by the couples' self-selection to be similar, meaning that even if spillovers were generally stronger among them, we may not necessarily observe them, as their behavior is already more aligned than among other cohabiting tenants. Nevertheless, the magnitude and nature of the social spillovers in our settings likely differ substantially from those arising between people who are more remotely connected.

Table 2: Distribution of donations within pairs

Panel A: Donation rate of a focal donor conditional on whether the peer donates		
	Peer does not donate	Peer donates
Donation rate of the focal donor	22.20%	53.87%

Panel B: Distribution of donations within pairs			
	Both donate	One donates	Nobody donates
Donation	(1,1)	(1,0) & (0,1)	(0,0)
Empirical distribution:	17.50%	29.98%	52.52%
Distribution under independence:	10.56%	43.86%	45.58%
χ^2-test for independent donations within pairs: $p < 0.001$			

donations, 30% show one donation, and 52.5% have no donations. Note that there are significantly more pair-observations with either both donors or no donor donating than expected under independence (χ^2-test for independent donations within pairs, p-value $\leq$ 0.001). Thus, donations within pairs are significantly positively correlated.

2.3 Instrument for Identification

Besides the regular invitation procedure, the BTSRC applies a phone call to a random subset of invited donors to increase turnout for blood types that are in short supply. Depending on the daily inventory in its blood stock, which is subject to random fluctuations in supply and demand, the BTSRC determines which of the blood types, A-, A+, O-, or O+, are in short supply. Subsequently, it uses a software to put a random subset of invited donors with matching blood types on a call list two days ahead of the blood drive.[9] The phone call informs the donors that their respective blood types are currently in short supply and encourages them to make a donation at the upcoming blood drive they are invited to. It is administered during office hours to the donors' cell phones and the voice message reads: "Your blood type X is in short supply, please come and donate at the upcoming blood drive."

Figure 1 illustrates how the invitation procedure and the randomized phone call result in a quasi-experimental design. In step **A**, all registered donors who are eligible for donation receive a personalized invitation letter several weeks before the blood drive. In step **B**, if the invited donors' blood types are in particularly short supply two days before

[9]We apply a strict intention-to-treat (ITT) methodology regarding the phone call: we only consider whether a call to the donor was attempted, not whether the call was answered in person, whether a message was left on the answering machine, or whether the call went unnoticed. This ITT approach only affects the interpretation of the direct effect of the phone call, but not the identification of the spillovers.

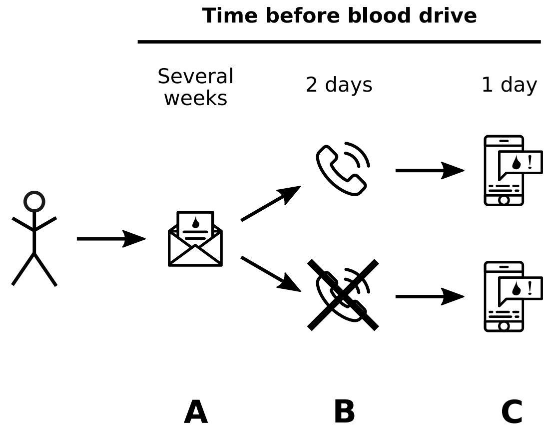

Figure 1: Illustration of the quasi-experimental design

Table 3: Descriptive statistics of the phone call

	Mean	Std. Dev.
Phone call	0.079	0.269
Share of pair-observations without phone call		85.72%
Share of pair-observations with 1 phone call		12.85%
Share of pair-observations with 2 phone calls		1.44%
Correlation of phone calls within pairs		0.113
# of pair-observations		13,421

the blood drive, they are randomly allocated to a treatment group receiving the phone call. Finally, in step **C**, one day before the blood drive takes place, all invited donors – regardless of whether they received the phone call or not – get a text message on their cell phones reminding them about the upcoming blood drive. It is important to notice that the phone call (step **B**) occurs between the invitation letter (step **A**) and the text message reminder (step **C**). Thus, the phone call contains no additional information about blood donations or blood drives beyond what is already mentioned in the invitation letter and the text message reminder.

As reported in Table 3, the incidence of the phone call among individual observations is 7.9%. Both donors received the phone call in 1.4% of the pair-observations, only one donor received the phone call in 12.9% of the pair-observations, and none of the donors received the phone call in 85.7% of the pair-observations. The phone calls are barely correlated within the pairs.

To be a valid instrument for identifying spillovers in the propensity to donate, the phone call needs to satisfy the exclusion restriction. Thus, we need to assert that the phone call is exogenous with respect to the peer's propensity to donate. In other words, a phone call to a donor must not affect the peer's propensity to donate directly, but only indirectly via its impact on the focal donor's propensity to donate. This is guaranteed by the institutional set-up. The BTSRC reaches the donors during office hours on their cell phones. Thus, the phone call cannot affect the peer who is most likely not present at that time.[10]

As mentioned before, the phone call is randomized conditional on the donors' blood types. We now verify that the randomization is well-balanced. Columns 1-3 in Table 4 show the randomization checks in the sample we use for the analyses, with increasing numbers of fixed effects. Columns 4-6 show the randomization checks separately for each blood type. All columns confirm that, conditional on blood types, the phone call is not correlated with other individual characteristics. The correlations of the phone call with gender and age are tiny and insignificant. Most importantly, the phone call is uncorrelated with the donation histories in the year prior to the study of both the focal donors as well as their peers. The corresponding coefficients are jointly insignificant in every specification.

2.4 Descriptive Evidence

In this subsection, we first provide some descriptive evidence of the phone call's effects on donors' propensity to donate. Subsequently, we use these effects to compute the Wald estimator that isolates the extent to which the propensity to donate spills over within pairs of donors. Hence, the analysis in this subsection illustrates the key feature in our data that will later drive the identification in the econometric model. Notice that, in contrast to the econometric model, it neglects control variables and the standard errors do not take into account that each pair is observed multiple times.

Figure 2 shows the average effect of the phone call on donation rates. It provides a first glimpse at the direct effect and reduced-form effect of the phone call on donors' motivation. Panel a) exhibits the average change in the focal donors' donation frequency if they receive a phone call: The donation frequency is 31 percent for donors who do not receive a phone call, and increases by 13 percentage points if they get a call. This is the direct effect of the phone call on donors' prosocial motivation. Panel b) exhibits the average change in the focal donors' donation frequency if their peers receive a phone call: it increases by roughly 5 percentage points, with the confidence intervals sufficiently far apart to suggest a significant relationship. This is the reduced-form effect of the peer's phone call on the focal donor's propensity to donate.

We can now obtain an estimate of the spillovers in the propensity to donate between the recipient of the phone call and the peer by applying the Wald estimator, i.e., we calculate

[10] Notice that our instrument only enables us to identify the spillovers within pre-existing pairs. Intuitively, our empirical strategy takes the social connection as given and examines how the behavioral impulse of the phone call feeds through it. An equally interesting, but distinct, research question would be to examine how the formation of pairs affects behavior. However, this is beyond the scope of this paper.

Table 4: Randomization checks of the phone call

Binary dependent variable: Received a phone call						
OLS Regression	(1)	(2)	(3)	(4)	(5)	(6)
	All sampled blood types			O-	O+	A-
Focal donor's characteristics						
Male	0.00131	0.000387	0.000330	0.0165	-0.00231	0.00690
	(0.00285)	(0.00267)	(0.00267)	(0.0134)	(0.00169)	(0.00853)
Age	5.26e-05	2.84e-05	2.70e-05	-0.000253	2.81e-05	0.000691*
	(8.84e-05)	(8.54e-05)	(8.52e-05)	(0.000406)	(6.42e-05)	(0.000372)
# of donations in year before study†						
1	-0.00308	-0.00400	-0.00190	-0.0122	-0.000547	-0.0134
	(0.00273)	(0.00269)	(0.00270)	(0.0129)	(0.00191)	(0.0104)
2	-0.00690*	-0.00711**	-0.00615*	-0.00344	-0.00151	-0.0163
	(0.00357)	(0.00349)	(0.00349)	(0.0154)	(0.00198)	(0.0123)
3	0.00421	0.00321	0.00380	-0.00209	0.00101	-0.0299
	(0.00858)	(0.00830)	(0.00822)	(0.0272)	(0.00493)	(0.0182)
4	0.0356	0.0395	0.0347		0.0398	
	(0.0508)	(0.0475)	(0.0453)		(0.0419)	
Blood types						
O-	0.687***	0.684***	0.684***			
	(0.0106)	(0.00981)	(0.00978)			
A+	-0.0111***	-0.0101***	-0.00993***			
	(0.00112)	(0.00131)	(0.00131)			
A-	0.212***	0.211***	0.210***			
	(0.00932)	(0.00859)	(0.00852)			
Peer's characteristics						
Male	0.00108	0.000156	9.89e-05	0.0157	-0.00221	0.00292
	(0.00285)	(0.00267)	(0.00267)	(0.0141)	(0.00167)	(0.00927)
Age	-1.47e-05	-3.89e-05	-4.03e-05	0.000555	0.000111*	-0.000243
	(9.17e-05)	(8.85e-05)	(8.82e-05)	(0.000376)	(6.41e-05)	(0.000342)
# of donations in year before study††						
1	-0.00309	-0.00401	-0.00192	-0.0154	-0.00279	0.00432
	(0.00284)	(0.00277)	(0.00276)	(0.0131)	(0.00185)	(0.00992)
2	-0.00311	-0.00332	-0.00237	0.00473	-0.00145	-0.00188
	(0.00347)	(0.00343)	(0.00342)	(0.0155)	(0.00194)	(0.0123)
3	0.00581	0.00481	0.00540	-0.000881	0.00463	0.00512
	(0.00733)	(0.00731)	(0.00726)	(0.0230)	(0.00458)	(0.0202)
4	-0.0351*	-0.0312	-0.0360		0.00122	
	(0.0212)	(0.0232)	(0.0244)		(0.00236)	
Blood types						
O-	0.0124**	0.0100*	0.0101*			
	(0.00576)	(0.00557)	(0.00556)			
A+	-0.00246	-0.00143	-0.00130			
	(0.00254)	(0.00243)	(0.00242)			
A-	-0.00298	-0.00434	-0.00479			
	(0.00565)	(0.00551)	(0.00550)			
Constant	0.0145***	0.0161***	0.0139***	0.695***	0.0155***	0.227***
	(0.00384)	(0.00364)	(0.00359)	(0.0165)	(0.00235)	(0.0131)
F-test for joint significance (p-value):						
† Own donation history dummies	0.282	0.201	0.359	0.774	0.800	0.329
†† Peer's donation history dummies	0.284	0.312	0.466	0.485	0.303	0.948
174 Location FEs?	no	yes	yes	yes	yes	yes
20 Month FEs?	no	no	yes	yes	yes	yes
# of individual observations	26,842	26,842	26,842	2,120	11,000	2,234
R-squared	0.507	0.526	0.539	0.508	0.296	0.569

Household cluster-robust standard errors in parentheses. Levels of significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Age normalized to sample average. The reference group consists of Female, 0 donations in the year before the study, and blood type O+.

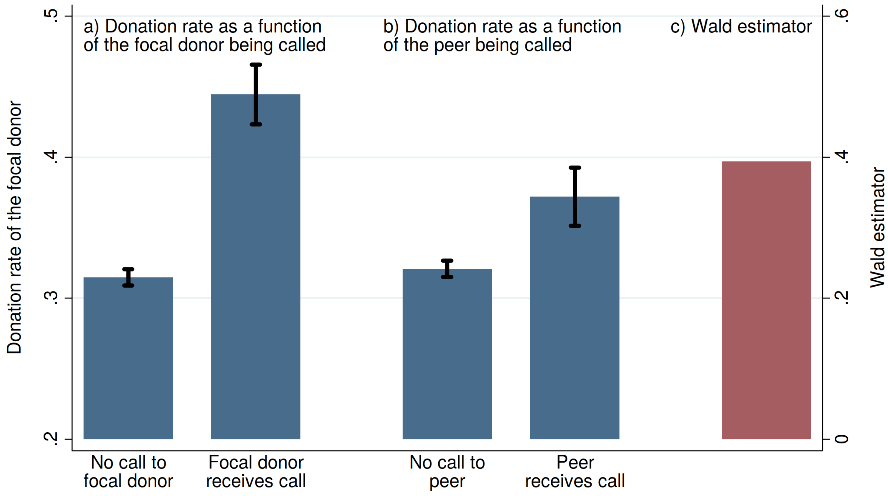

Figure 2: The Wald estimator of spillovers in the propensity to donate: donation frequency as function of the own phone call (panel a) and the peer's phone call (panel b). Bars indicate 95% confidence intervals.

the ratio between the phone call's reduced-form effect and its direct effect, which amounts to roughly $5\%/13\% = 38\%$.[11] This suggests that spillovers play an important role in pairs of donors. In each round, about 38% of a given change in the recipient's propensity to donate spills over to her peer.

3 Econometric Analysis

This section presents the econometric analysis of identifying spillovers in the propensity to donate. We first introduce the structural model, then formally discuss the identification strategy, and finally outline the estimation procedure.

3.1 Structural Model

In the structural model, the propensity of donor i in pair p to donate blood is

$$Y^*_{ip} = \beta_0 + \delta Y^*_{-ip} + \beta_1' X_{ip} + \beta_2' X_{-ip} + \epsilon_{ip}\,. \tag{3.1}$$

For notational convenience, we drop the subscript t for the invitation to an upcoming blood drive at time t in this subsection. β_0 is a constant, measuring the baseline motivation to donate. The key term in the model is the spillover parameter δ of the propensity to donate Y^*_{-ip} of the peer. In Appendix A.1, we provide a microfoundation for this structural model. We consider a simultaneous-move game of the pair, fashioned after the

[11]The Wald estimator ω of an endogenous regressor s_i using the binary instrument z_i is given by $\omega = \frac{E[y_i|z_i=1]-E[y_i|z_i=0]}{E[s_i|z_i=1]-E[s_i|z_i=0]}$ (Angrist and Pischke 2008).

Battle of the Sexes game, in which there is a motivational complementarity: the benefit from donating to the focal donor i increases if the peer $-i$ donates. This complementarity could arise from enjoyment of shared experiences, reduced transportation cost, peer pressure, or image motivation. As we show, in equilibrium, donors act as if there was a direct spillover where Y^*_{-ip} enters the utility function as described in Equation 3.1. We refer to these mechanisms summarily as "motivational complementarities" as they all share the property that they generate a policy multiplier of the same structure. The vector X_{ip} represents donor i's characteristics, including her gender, age, blood type, and dummies for the number of donations she made during the year prior to the study. The vector X_{-ip} includes the same set of characteristics of i's peer.

Since the decision on whether or not to donate, Y_{ip}, is binary and we study pairs of donors, we can estimate a bivariate probit model to capture the simultaneous decision-making of the two donors in each pair as in Equations 3.2 and 3.3.

$$Y^*_{1p} = \beta_0 + \delta Y^*_{2p} + \beta_1' X_{1p} + \beta_2' X_{2p} + \epsilon_{1p} \tag{3.2}$$

$$Y^*_{2p} = \beta_0 + \delta Y^*_{1p} + \beta_1' X_{2p} + \beta_2' X_{1p} + \epsilon_{2p} \tag{3.3}$$

$$\begin{aligned} Y_{1p} &= 1 \quad \text{if} \quad Y^*_{1p} > 0, \quad \text{and} \quad Y_{1p} = 0 \quad \text{otherwise} \\ Y_{2p} &= 1 \quad \text{if} \quad Y^*_{2p} > 0, \quad \text{and} \quad Y_{2p} = 0 \quad \text{otherwise} \end{aligned}$$

We assume the random errors ϵ_{1p} and ϵ_{2p} to be bivariate normally distributed, with $\mathrm{E}(\epsilon_{1p}) = \mathrm{E}(\epsilon_{2p}) = 0$, $\mathrm{Var}(\epsilon_{1p}) = \mathrm{Var}(\epsilon_{2p}) = 1$, and $\mathrm{Cor}(\epsilon_{1p}, \epsilon_{2p}) = \rho$. The correlation between the random errors, ρ, captures potentially omitted exogenous effects, such as health status and education, as well as correlated effects, such as sharing a common environment.

Substituting equation 3.3 into 3.2 yields the reduced form,

$$Y^*_{1p} = \frac{\beta_0 + \delta\beta_0}{1-\delta^2} + \frac{\beta_1' + \delta\beta_2'}{1-\delta^2} X_{1p} + \frac{\delta\beta_1' + \beta_2'}{1-\delta^2} X_{2p} + \frac{\delta\epsilon_{2p} + \epsilon_{1p}}{1-\delta^2}\,. \tag{3.4}$$

and the analogous expression for the peer:

$$Y^*_{2p} = \frac{\beta_0 + \delta\beta_0}{1-\delta^2} + \frac{\beta_1' + \delta\beta_2'}{1-\delta^2} X_{2p} + \frac{\delta\beta_1' + \beta_2'}{1-\delta^2} X_{1p} + \frac{\delta\epsilon_{1p} + \epsilon_{2p}}{1-\delta^2}\,. \tag{3.5}$$

The equations highlight the identification problem: we have three independent variables (the constant, X_{1p}, and X_{2p}), but four unknown parameters (β_0, β_1, β_2, and δ).[12]

[12] If we assumed that $\rho = 0$, then the functional form induced by the normality assumption over the errors in the structural form, ϵ_{1p} and ϵ_{2p}, would allow us to identify δ. To see why this is true, note that the error terms in the reduced form, (3.4) and (3.5), are linear combinations of the errors ϵ_{1p} and ϵ_{2p} in the structural form. Thus, when $\rho = 0$, we could identify δ off the correlation of the error terms in the reduced form. However, when $\rho \neq 0$, this in itself introduces a correlation in the errors in the structural form, leaving δ unidentified. In our context, ρ could reflect omitted exogenous effects

3.2 Indentification

The above identification problem can be resolved by using an instrument, in our context, the phone call discussed in subsection 2.3. Within our model, it takes on the role akin to an instrument in a TSLS estimation. Denote P_{ip} by the binary variable indicating whether donor i in pair p received a phone call for the current invitation. As mentioned above, a critical feature of the phone call is that it directly affects donor i's propensity to donate, but not that of her peer. The econometric model then becomes

$$Y^*_{1p} = \beta_0 + \gamma P_{1p} + \delta Y^*_{2p} + \beta_1' X_{1p} + \beta_2' X_{2p} + \epsilon_{1p} \tag{3.6}$$

$$Y^*_{2p} = \beta_0 + \gamma P_{2p} + \delta Y^*_{1p} + \beta_1' X_{2p} + \beta_2' X_{1p} + \epsilon_{2p} \tag{3.7}$$

Substituting equation 3.7 into 3.6 yields the following reduced form:

$$Y^*_{1p} = \frac{\beta_0 + \delta\beta_0}{1-\delta^2} + \frac{\gamma}{1-\delta^2} P_{1p} + \delta\frac{\gamma}{1-\delta^2} P_{2p} + \frac{\beta_1' + \delta\beta_2'}{1-\delta^2} X_{1p} + \frac{\delta\beta_1' + \beta_2'}{1-\delta^2} X_{2p} + \frac{\delta\epsilon_{2p} + \epsilon_{1p}}{1-\delta^2} \tag{3.8}$$

Note that, just like in the theoretical model in Section A.1 in the Appendix, the impact of the phone call P_{1p} on donor 1's propensity to donate is given by $\frac{\gamma}{1-\delta^2}$ because of the spillovers that go back and forth between the two donors: A fraction δ of the initial impulse to donor 1 also affects donor 2, which in turn feeds back into donor 1's propensity to donate, and so on. This amplifies the response to the phone call if $0 < \delta < 1$. For donor 2, the overall effect amounts to $\delta\frac{\gamma}{1-\delta^2}$, as only a fraction δ of donor 1's propensity to donate spills over to donor 2 (and because donor 1's phone call has no direct effect on donor 2's propensity to donate – this is the exclusion restriction needed to identify the spillovers). This allows us to identify the parameter δ by dividing the reduced-form coefficient of donor 2's phone call by the reduced-form coefficient of donor 1's phone call.[13] Having obtained δ, we can identify all remaining structural parameters: as is obvious from the reduced form above, all other structural parameters are uniquely identified once δ is recovered (see Section A.4 in the Appendix on how to recover the structural parameters and calculate their standard errors).

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or unobservable common shocks to the motivation to donate stemming from similar environments, thus making identification suspect if one imposed $\rho = 0$ ex-ante.

[13] Notice also that the fact that γ has an intention-to-treat interpretation is irrelevant for the purposes of identifying the structural parameter δ.

3.3 Estimation

We estimate the parameters of the bivariate probit model, $\theta = (\beta_0, \beta_1', \beta_2', \gamma, \delta, \rho)'$, using the method of maximum likelihood. Pair p's contribution to the model's density is

$$f(\theta; P_p, X_p, Y_p) = \prod_{t=1}^{T_p} \Phi_2\left(w_{1pt}, w_{2pt}, \rho_{pt}^*\right) , \tag{3.9}$$

where $w_{ipt} = q_{ipt}Y_{ipt}^*$, $q_{ipt} = 2Y_{ipt} - 1$, $\rho_{ht}^* = q_{1pt}q_{2pt}\rho_{pt}$, and Φ_2 is the cumulative distribution function of the bivariate normal distribution (Greene 2003). Equation 3.9 directly yields the model's log likelihood,

$$\ln L(\theta; P_p, X_p, Y_p) = \sum_p \ln f(\theta; P_p, X_p, Y_p) . \tag{3.10}$$

As the T_p observations of pair p may be serially correlated, we estimate pair cluster-robust standard errors using the sandwich estimator (Huber 1967; Wooldridge 2002). To control for potential heterogeneity across the locations and months of the blood drives, we include location and month fixed effects.

4 Results

In this section, we present the results of the econometric analysis. First, we discuss the estimated coefficients of the bivariate probit model in our baseline specification which allows us to identify spillovers in the propensity to donate. Subsequently, we show evidence that the spillovers are unlikely to be exclusively driven by the transmission of information (about the scarcity of a certain blood type or the blood drives) but rather by motivational complementarities. Finally, we quantify the social multiplier and confirm that it does not erode over time due to intertemporal substitution effects.

4.1 Estimated Coefficients of the Bivariate Probit Model

Table 5 shows the estimated coefficients for the structural equation in three different specifications of the bivariate probit model.[14] Column (1) shows the estimates of the specification without fixed effects. Column (2) shows the estimates of the specification with location fixed effects, while the specification in column (3) additionally controls for month fixed effects. We add fixed effects to avoid confounds that may arise since the blood drives took place at different locations and points in time, which may affect both donors in a pair similarly. The 174 location fixed effects absorb differences between urban

[14]For first stage F-statistics regarding the strength of the instrument, please refer to the 2SLS specification in Appendix A.2.

Table 5: Bivariate probit model

Binary dependent variable: donation decision (0,1)			
Bivariate probit regression	(1)	(2)	(3)
Phone call (γ)	0.220***	0.222***	0.216***
	(0.060)	(0.061)	(0.058)
Spillovers in the propensity to donate (δ)	0.464***	0.460***	0.412**
	(0.159)	(0.163)	(0.176)
Constant (β_0)	-0.537***	-0.686***	-0.678***
	(0.160)	(0.226)	(0.239)
Focal donor's characteristics (β_1)			
Male	0.118***	0.097***	0.116***
	(0.018)	(0.019)	(0.019)
Age	0.011***	0.012***	0.012***
	(0.001)	(0.001)	(0.001)
# of donations in year before study			
1	0.529***	0.551***	0.560***
	(0.027)	(0.027)	(0.027)
2	0.887***	0.942***	0.952***
	(0.032)	(0.035)	(0.035)
3	1.096***	1.191***	1.204***
	(0.058)	(0.063)	(0.063)
4	0.901***	0.997***	0.989***
	(0.113)	(0.128)	(0.129)
Blood types			
O-	0.041	0.042	0.048
	(0.054)	(0.055)	(0.054)
A+	-0.023	-0.021	-0.021
	(0.021)	(0.022)	(0.022)
A-	0.035	0.048	0.048
	(0.041)	(0.041)	(0.041)
Peer's characteristics (β_2)			
Male	-0.036	-0.043	-0.037
	(0.027)	(0.027)	(0.028)
Age	-0.006***	-0.006***	-0.006***
	(0.002)	(0.002)	(0.002)
# donations in year before study			
1	-0.261***	-0.259***	-0.226**
	(0.086)	(0.093)	(0.102)
2	-0.415***	-0.398**	-0.348**
	(0.143)	(0.160)	(0.174)
3	-0.520***	-0.460**	-0.398*
	(0.183)	(0.212)	(0.229)
4	0.391	-0.318	-0.283
	(0.314)	(0.322)	(0.333)
Blood types			
O-	-0.057	-0.058	-0.049
	(0.050)	(0.052)	(0.054)
A+	0.009	0.011	0.010
	(0.022)	(0.022)	(0.022)
A-	-0.081**	-0.080**	-0.076*
	(0.037)	(0.040)	(0.040)
ρ (correlation between errors in the structural form)	-0.392	-0.418	-0.321
	(0.342)	(0.342)	(0.380)

Wald-tests for joint significance (p-values)			
Focal donor:			
all blood types	0.42	0.37	0.34
negative blood types	0.64	0.49	0.46
non O-negative blood types	0.28	0.22	0.22
Peer:			
all characteristics	0.07	0.09	0.14
previous donations	0.06	0.04	0.17
all blood types	0.13	0.16	0.23
negative blood types	0.09	0.12	0.16
174 Location FEs?	no	yes	yes
20 Month FEs?	no	no	yes
# of pairs	5,053	5,053	5,053
# of pair observations	13,421	13,421	13,421
Log likelihood	-15,022.06	-14,667.67	-10,884.40

Household cluster-robust standard errors in parentheses.
Levels of significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$
Age normalized to sample average.

and rural areas as well as differences between the local organizers of the blood drives. The 20 month fixed effects pick up seasonal fluctuations or special events that may influence donation rates, such as school holidays.

First, we examine the direct effect of the phone call on the probability to donate. The coefficient γ is positive, and estimated with considerable precision, with a z-statistic of well above 2. This coefficient represents the impact of the phone call on donor's motivation if the donor were not part of a pair. The magnitude of the coefficient alone cannot be interpreted, but we can calculate the marginal effect of the phone call on the probability to donate.[15] We find that the marginal effect is 8.7 percentage points, which is very close to the estimate in Bruhin et al. (2015) that uses all donors in the sample. Thus, focusing on pairs does not appear to lead to a selection of donors who are generally more receptive to nudges to donate.

Next, we examine the extent of spillovers in the propensity to donate within pairs of donors, δ. In contrast to the other probit coefficients, δ has an interpretation of a marginal effect because it is calculated as the ratio of two reduced form parameters.[16] It is highly significant in all three specifications. It is equal to 0.46 in the baseline specification of column (1). This implies that 46 percent of a one-unit increase in the peer's propensity to donate spills over to the other donor in the pair. Hence, a donor's propensity to donate blood strongly depends on her peer's propensity to donate. The estimates are slightly lower in columns (2) and (3) which also include the location and month fixed effects. But even in the strictest specification of column (3), the parameter is equal to 0.41, implying that 41 percent of a peer's propensity to donate spill over to the other donor in the pair. We also examine whether the estimate of the social multiplier is sensitive to the choice of the functional form. In the Appendix A.2, we re-estimate our model as a linear

[15] We show how we calculate the marginal effect of the probit coefficients in Section A.5 in the Appendix.
[16] See Appendix A.4 for details.

probability model, using the phone call to the peer as an instrument for her donation. The results are virtually identical.

Individual characteristics are strong determinants of the probability to donate. Male donors are significantly more likely to donate blood than female donors. This gender difference is robust and quantitatively important. The marginal effect of being male on the probability to donate is 4.5 percentage points, again an effect that is roughly similar to the difference found in Bruhin et al. (2015). Donation rates also increase significantly with age. Increasing age by one year increases the probability to donate by 0.5 percentage points. This finding is robust across all three specifications and consistent with the result in many other studies (Wildman and Hollingsworth 2009; Lacetera, Macis and Slonim 2012a, 2014). As in Wildman and Hollingsworth (2009) we find that the number of donations in the year before entering the study predicts current blood donations: The coefficients for the number of donations made prior to the study reveal that previous regular donors are more likely to donate than previous irregular donors. Finally, blood types have no significant effect on donation rates (Wald-test for joint significance of all blood types, $p > 0.3$ in all specifications). In particular, donors with highly demanded, negative blood types do not donate more frequently (Wald-test for joint significance of negative blood types, $p > 0.4$ in all specifications).

There are some negative correlations between peer's characteristics and the focal donor's motivation. While we control for the peer's characteristics in the regression, the coefficients of these characteristics do not have a causal interpretation as the pairs are not randomly assigned.

Finally, the estimates of the correlation of the errors in the structural model, ρ, lie between -0.32 and -0.42, depending on the specification, and are estimated with little precision: in each of the specifications, the standard error is roughly 0.4.[17]

4.2 Motivational Complementarities vs. Transmission of Information

Previous studies have concluded that some observed social interaction effects are due to the transmission of information (Lacetera, Macis and Slonim 2014; Bond et al. 2012; Drago, Mengel and Traxler 2013). In our context, transmission of information and motivational complementarities are both possible. Spillovers could emerge from the motivational impulse of the phone call to the peer, as postulated by our econometric model.[18] However, it is also possible that the information conveyed by the phone call about the

[17] However, the results are not sensitive to the estimation of ρ, as in Appendix A.6 we show that the results remain robust when we restrict ρ to 0. This does not indicate that including ρ is unnecessary as - ex ante - it is impossible to know whether there is a systematic correlation between the residuals.

[18] As we mentioned before, motivational complementarities are very broadly defined in our set-up. We discuss this in more detail in the theoretical model in Appendix A.1.

blood drive or the scarcity of the specific blood type is transmitted within the pair and that donors respond to this information.

Fortunately, our set-up allows us to check for the presence of motivational complementarities besides such an informational channel with two tests. We conduct these tests in the context of the reduced form of the bivariate probit model since these mechanisms would invalidate the exclusion restriction needed for the structural model in Section 3.1. Our first check tests whether the phone call transmits information about the scarcity of a specific blood type to the other member of the pair. Recall that the phone call is made as a function of the scarcity of certain blood types, and this information is conveyed to the potential donors very clearly. If it were information about the scarcity that is transmitted between donors, then this effect should be stronger if they have compatible blood types.[19] We augment the reduced form in the bivariate probit model by adding the indicator $C_p = 1$ if a focal donor's blood type is compatible with the peer's blood type, and $C_p = 0$ otherwise. We add the interaction between C_p and the peer's phone call, and estimate

$$Y^*_{ip} = \kappa_0 + \kappa_1 P_{ip} + \kappa_2 P_{-ip} + \kappa_3 C_p + \kappa_4 C_p \times P_{-ip} + \kappa'_5 X_{ip} + \kappa'_6 X_{-ip} + u_{ip}\,. \qquad (4.1)$$

If information about the scarcity of the blood type were transmitted between donors, we would expect κ_2 to vanish, or at least diminish relative to the baseline specification, and κ_4 to be significantly positive.

Table 6 displays the results. Columns (1) and (2) show the reduced forms of the baseline specification with and without the indicator C_p. Column (3), labeled "Test 1a", exhibits the estimates of Equation (4.1). As can be seen, the coefficients and standard errors on one's own phone call and the peer's phone call remain virtually unchanged. Furthermore, the interaction with the compatible blood type to the peer is not statistically significant. Therefore, there is no evidence that information about the scarcity of the blood type is transmitted, as donors with incompatible blood types (which are not scarce at the moment), are no less affected by a phone call to their peers. Arguably, donors might be less familiar with the compatibility of different blood types than the recognition of same blood types. Columns (4) and (5) show the same analysis using identical blood types within pairs (indicated by the binary variable S_p) and its interaction with the peer's phone call indicator. The results show again there is no evidence that information about the specific scarcity of the blood type is transmitted within pairs in a way that affects donation decisions.

[19] Compatibility in blood types works as follows. Donors with blood type O are universal donors and can give to everyone. Donors with blood type A can give to donors with blood types A and AB. Donors with blood type B can give to donors with blood types B and AB. Donors with blood type AB can only give to other donors with blood type AB. Regarding the Rh factor, donors with negative blood types can donate to donors with negative and positive blood types but donors with positive blood types can only give to other donors with positive blood types.

Table 6: Bivariate probit model, reduced forms

Binary dependent variable: donation decision (0,1)						
	(1)	(2)	(3)	(4)	(5)	(6)
Bivariate probit regression	Original Model	Augmented Original Model a	Test 1a	Augmented Original Model b	Test 1b	Test 2
	(Eq. 3.8)	(Eq. 3.8 aug.)	(Eq. 4.1)			(Eq. 4.2)
P_{1p}	0.260***	0.260***	0.269***	0.261***	0.259***	0.263***
	(0.044)	(0.044)	(0.045)	(0.044)	(0.045)	(0.048)
P_{2p}	0.107**	0.107**	0.123**	0.108***	0.106**	0.111**
	(0.046)	(0.046)	(0.050)	(0.046)	(0.048)	(0.049)
C_p		-0.011	-0.004			
		(0.041)	(0.043)			
$C_p \times P_{2p}$			-0.078			
			(0.095)			
S_p				-0.032	-0.033	
				(0.026)	(0.027)	
$S_p \times P_{2p}$					0.015	
					(0.108)	
$P_{1p} \times P_{2p}$						-0.017
						(0.097)
$\bar{\rho}$	0.496***	0.496***	0.496***	0.496***	0.496***	0.496***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
# of pairs	5,053	5,053	5,053	5,053	5,053	5,053
# of pair observations	13,421	13,421	13,421	13,421	13,421	13,421
Log likelihood	-14,625.78	-14625.72	-14,625.37	-14,624.64	-14,624.63	-14,625.76

Models additionally include reduced form parameters for X_{1p} and X_{2p} and absorb 174 location and 20 month fixed effects.
Pair cluster robust standard errors in parentheses. Age normalized to sample average.
The shown variables have the following interpretation: The binary variables P_{1p} and P_{2p} indicate the phone calls to the focal donor and the peer. The binary variable C_p indicates whether the focal donor's blood type is compatible to the peer's blood type. The binary variable S_p indicates if the focal donor and the peer have the same blood type. $\bar{\rho}$ is the correlation between the reduced form error terms.
Levels of significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Our second test is based on the intuition that the phone call to one donor may simply serve as a reminder of the blood drive to the other donor in the pair. This is possible despite the fact that it takes place between the invitation letter and the text message that every invited donor receives. In this case, a phone call to the peer should have less of an effect on the focal donor if she received a phone call as well. This can be tested by augmenting the reduced form by an interaction between the two phone calls $P_{ip} \times P_{-ip}$ and the coefficient of the interaction should be significantly negative. Thus, we estimate the equation

$$Y_{ip}^* = \xi_0 + \xi_1 P_{ip} + \xi_2 P_{-ip} + \xi_3 P_{ip} \times P_{-ip} + \xi_4' X_{ip} + \xi_5' X_{-ip} + v_{ip}\,. \tag{4.2}$$

The results of this test are displayed in Column (6), labeled "Test 2" in Table 6. As can be seen, the point estimate of the coefficient of the peer's phone call remains positive and significant. The point estimate of the interaction of the two phone calls is small and insignificant. Hence, we find no evidence that the phone call merely serves as a reminder for the blood drive.

In summary, neither form of information transmission (information about scarcity of a particular blood type or general reminder of the blood drives) can account for our findings of spillovers in the propensity to donate. We interpret these results as corroboration of our interpretation of motivational complementarities generating the spillovers.

4.3 The Social Multiplier

Given the significant spillover effects, we now quantify their impact in terms of a multiplier on a given policy intervention that affects a donor's propensity to donate. Consider how the phone call to donor 1 changes her propensity to donate Y_1^*: its effect depends both on the phone call, and on the feedback induced by her peer, donor 2. Thus, $\Delta Y_1^* = \gamma + \delta \Delta Y_2^*$. Similarly, the peer is affected indirectly and her propensity to donate increases by $\Delta Y_2^* = \delta \Delta Y_1^*$. Solving this system of two equations yields $\Delta Y_1^* = \gamma/(1-\delta^2)$ and $\Delta Y_2^* = \gamma\delta/(1-\delta^2)$. Thus, the social amplification is $1/(1-\delta^2)$ for the donor receiving the call, and a fraction δ of that for the peer, for a total effect of $1/(1-\delta^2) + \delta/(1-\delta^2) = 1/(1-\delta)$.

Our baseline estimate of $\delta = 0.46$ implies a substantial social multiplier. The spillovers amplify the effectiveness of the phone call for the donor called by a factor of $1/(1-0.46^2) = 1.27$, and therefore by $0.46/(1-0.46^2) = 0.58$ for her peer, donor 2. Overall, this creates a social multiplier, equal to the sum of the two effects of $1/(1-0.46) = 1.85$. Even in the strictest specification, our estimate of δ is 0.41, implying a social multiplier of $1/(1-0.41) = 1.7$.

We now illustrate how the social multiplier increases the effect of a policy intervention, again using the example of the phone call in our study. Recall that in Section 5.1, we pointed out that in the absence of motivational complementarities, a phone call would increase the propensity to donate by 8.7 percentage points. With our baseline estimate of $\delta = 0.46$, the spillovers amplify the effect of the phone call on the target donor to 11 percentage points, and also create a spillover, amounting to a 5 percentage points increase in the probability to donate on the peer. Overall, this results in a 16 percentage points increase in blood donation.[20] Thus, in the absence of such spillovers, the BTSRC would have to call $1/0.087 \approx 11$ donors to increase expected turnout at the blood drive by 1. In contrast, if the BTSRC called a member of a pair, only $1/(0.16) \approx 6$ phone calls are necessary for the same increase.

If the BTSRC is exclusively interested in a particular blood type – as blood transfusions have a limited shelf life and disposing them is costly (Garbarino et al. 2017) – calculations would look slightly different. Assume the BTSRC only cares about increasing the turnout of donors with O-negative blood type who make up just 8% of our sample. As mentioned before, taking into account the social multiplier, every phone call increases the probability to donate of the focal donor by 11 percentage points and also increases the probability to donate of the peer by 5 percentage points. Therefore, in order to increase the turnout by 10 additional donors with O-negative blood type, assuming that the blood types of peers are independent, the BTSRC needs to call $10/(0.11 + 0.08 \times 0.05) \approx 88$ donors with O-negative blood type. However, at the same time, $88 \times (1 - 0.08) \times 0.05 \approx 4$ additional donors with other blood types will also turn up in response to these 88 phone calls. The BTSRC should take this into account and adjust its overall recruitment schedule accordingly.

4.4 Intertemporal Substitution

One potential concern about the robustness of our estimated social multiplier are intertemporal substitution effects. It is conceivable that donations in response to the behavior of one's peer draw on blood donations which that donor would have given in the future, akin to intertemporal substitution of labor. This would change the interpretation of the multiplier, as the higher impact today would be offset by a predictable drop in donations in the future.

We test for intertemporal substitution in the reduced form of the bivariate probit model by including past phone calls (indexed $t-1$) of the focal donor and her peer[21],

$$Y^*_{ip,t} = \mu_0 + \mu_1 P_{ip,t} + \mu_2 P_{-ip,t} + \mu_3 P_{ip,t-1} + \mu_4 P_{-ip,t-1} + \mu_5' X_{ip,t} + \mu_6' X_{-ip,t} + \upsilon_{ip,t} \,. \quad (4.3)$$

[20] These estimated direct effects of the phone call are much more aligned with previous estimates among (mostly) unconnected donors (Bruhin et al. 2015), than our naive estimates in Figure 2. Thus, the estimated magnitude of the social multiplier fits the data remarkably well.

[21] Estimating the structural model is not feasible because this would mean estimating a multivariate probit model and would force us to drop almost 40% of the observations due to the need of lagged donation variables in order to model the intertemporal correlations in residuals.

Table 7: Long-term effects in the reduced form probit model

Binary dependent variable: donation decision (0,1)			
Probit regression (marginal effects)	(1)	(2)	(3)
Focal donor's phone call (μ_1)	0.0937***	0.0914***	0.0842***
	(0.0140)	(0.0140)	(0.0142)
Peer's phone call (μ_2)	0.0461***	0.0442***	0.0370**
	(0.0144)	(0.0145)	(0.0146)
Focal donor's past phone call (μ_3)	0.00688	0.00625	0.0140
	(0.0143)	(0.0140)	(0.0142)
Peer's past phone call (μ_4)	-0.00729	-0.00888	-0.00104
	(0.0139)	(0.0138)	(0.0139)
174 Location FEs?	no	yes	yes
20 Month FEs?	no	no	yes
# of pairs	5,053	5,053	5,053
# of pair observations	13,421	13,421	13,421
Log likelihood	-15,686.86	-15,228.8	-15,173.97

Models additionally include reduced form parameters for X_{1p}, X_{2p}, and a constant.
Household cluster-robust standard errors in parentheses.
Levels of significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$
Age normalized to sample average.

If there was intertemporal substitution, one would expect the coefficient μ_4 to be significantly negative.

Table 7 displays the regression results. The effects of the focal donor's and the peer's present phone calls on the current donation rate are not influenced by the past phone calls. The estimated coefficients of the current phone calls are still large and highly significant. In contrast, the past phone calls have no effect on the current donation rate. The estimated coefficients are very small and insignificant.

In conclusion, we find no evidence that the spillovers behind the social multiplier are affected by intertemporal substitution. Hence, the estimated social multiplier does not produce a drop in donations in the future.

5 Conclusion

In this paper we use a large panel data set with a quasi-randomized phone call to analyze the role of spillovers in the propensity to donate blood within pairs of pre-registered donors. We find strong evidence that these spillovers have a forceful impact on donor motivation, as they generate a social multiplier that amplifies the direct impact of policy interventions by 70 to 85 percent. Using the phone call as an example of a policy intervention, in order to generate an additional 100 blood donations, the BTSRC only needs to call between 625 and 676 donors, compared to 1149 donors in the absence of motivational complementarities.

Graham (2011) pointed out that social planning should take the presence of treatment spillovers into account. This is particularly important in the context of voluntary blood donations, where more is not always better as blood transfusions cannot be stored indefinitely and disposal is costly (Garbarino et al. 2017). As our calibration exercise in subsection 4.3 shows, the number of extra undesired donations caused by spillover effects can be substantial in a large-scale intervention. Therefore, blood donation services may want to minimize donations of undesired blood types. Our findings indicate that blood donation services have to be aware of how encouraging a valuable universal donor might also increase turnout of donors with undesired blood types. Hence they should target pairs of donors where both blood types are in high demand.

The policy implications are not confined to voluntary blood donations, but also apply to other donations in the public health domain such as organ donations (Becker and Elias 2007; Eames, Holder and Zambrano 2017; Byrne and Thompson 2001) and bone marrow donations (Bergstrom, Garratt and Sheehan-Connor 2009; Lacetera, Macis and Stith 2014). Furthermore, the policy implications of such spillovers can go beyond the health domain to fields such as volunteering, civic engagements, and welfare participation. Bond et al. (2012) find spillovers on political participation through an online community that are so strong that the indirect effects in the network are even larger than the direct effect of the intervention. Bertrand, Luttmer and Mullainathan (2000) find that higher contact availability in the social networks increases individuals' welfare participation. Mechanisms that exploit social networks and social ties are possible routes that could amplify traditional policy interventions aiming at increasing contributions to such public goods.

An important concern involves general substitution effects across different domains of prosocial behaviors. It is possible that increasing activity in one domain leads to substitution effects in others. Thus, at the societal level, our intervention may be less beneficial than the analysis of just one domain – blood donations – suggest. No studies we are aware of is able to identify such substitution effects. A challenge for future research is to generate accurate measurements of prosocial behaviors in different domains to allow the identification of such effects. Another avenue for future research is to investigate the extent to which spillovers in the propensity to donate blood also arise in larger social networks where the social ties between individuals are arguably weaker than within our pairs of co-resident couples.

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A Appendix

A.1 Theoretical Framework

In this section, we present a simple model to illustrate how spillovers arising from various motivational complementarities can increase blood donations and how it is mapped to our empirical set-up.

We consider a game between two players, denoted player 1 and player 2. Each has a benefit B from donating blood. The utility of not donating is normalized to zero. Importantly, there is a behavioral complementarity which can be spillovers arising from social interactions, joint consumption or any other externalities: If both players donate, the benefits are increased by $b \geq 0$ for each of them. The cost of donating blood is $\tilde{c}_i$ that is drawn from a uniform distribution $[0, C]$ for both players.

We further consider two versions of the game. In the first version, each player's draw of cost is only known to himself, though the distribution is common knowledge. This formulation is in keeping with other strategic interactions between connected individuals, such as the Battle of the Sexes game. In this case, it is a game of incomplete information, and has a unique mixed-strategy equilibrium with a straightforward interpretation in terms of our structural model. In particular, in this formulation of the game, individuals will act in equilibrium as if the propensity to donate directly entered their objective functions, and the parameter δ can be interpreted in terms of the parameters of the game. However, one may argue that players can communicate after they observe their private costs, turning the interaction into a sequential game. We illustrate this in the second version of the game. In this case, the game has a pure-strategy equilibrium. However, as we show below, averaging over individuals, this version of the game inherits all the properties of the first version of the game and also implies that the identification of the spillover parameter can be achieved as in our empirical model.

Version 1: incomplete information about $\mathbf{c_i}$.

In this version of the game, both players decide simultaneously whether or not to donate without knowing the other player's strategy. In trying to stay close to the empirical set-up, assume that player 2 receives a phone call which raises her utility from donating by γ (e.g. by making the benefits of donating more salient). For the sake of this application, we assume that player 1 knows about the extra utility γ to the other player. Player 1 will attend the blood drive if $B + p_2 b - c_1 \geq 0$, where p_2 is the probability that player 2 will also go to the blood drive. Similarly, player 2 will attend the blood drive if $B + \gamma + p_1 b - c_2 \geq 0$. Thus, p_2 is given by $p_2 = \Pr(c_2 \leq B + \gamma + p_1 b) = F_c(B + \gamma + p_1 b)$, and p_1 is given by $p_1 = \Pr(c_1 \leq B + p_2 b) = F_c(B + p_2 b)$, where F_c is the c.d.f. of the random costs c_i. Imposing the assumption of uniform distribution yields a system of linear equations in

p_1 and p_2:

$$p_2 = \frac{B + \gamma + p_1 b}{C} \text{ and } p_1 = \frac{B + p_2 b}{C} \tag{A.1}$$

Solving for p_1 and p_2, one obtains

$$p_1 = \frac{B}{C - b} + \gamma \frac{b}{C^2 - b^2} \text{ and } p_2 = \frac{B}{C - b} + \gamma \frac{C}{C^2 - b^2} \tag{A.2}$$

It is instructive to define $\delta \equiv \frac{b}{C}$ which, in this setting, corresponds to the probability that the utility cost of donating blood is less than or equal to the benefit from donating together. Substituting this term in the optimal donation probabilities, we obtain

$$p_1 = \frac{B}{C} \frac{1}{1 - \delta} + \frac{\gamma}{C} \frac{\delta}{1 - \delta^2} \text{ and } p_2 = \frac{B}{C} \frac{1}{1 - \delta} + \frac{\gamma}{C} \frac{1}{1 - \delta^2} \tag{A.3}$$

To see how spillovers arising from social interactions increase blood donations, consider the impact of the phone call on the two players' behavior. Player 2 receives the phone call, which raises her utility of donating by γ. Holding player 1's behavior constant, this translates into a change in player 2's probability of donating by $\frac{\gamma}{C}$, as can be seen from equation (A.1). However, player 1's behavior will not stay constant, since p_2 has increased. Equation (A.1) dictates that player 1 increase his probability of donating by $\frac{\gamma}{C} \frac{b}{C} = \delta \frac{\gamma}{C}$, holding player 2's behavior constant. This, in turn, leads player 2 to increase her probability of donating by $\delta^2 \frac{\gamma}{C}$, and so on. The resulting behavioral changes induce a geometric series with decay δ, yielding an equilibrium change in the donation probability of $\frac{\gamma}{C} \frac{1}{1-\delta^2}$ for player 2, and of $\frac{\gamma}{C} \frac{\delta}{1-\delta^2}$ for player 1, as can be verified in equations (A.3). Notice that the behavioral impulse to player 1 is scaled down by the factor $\delta < 1$ compared to that of player 2. Thus, the strategic structure put in place by spillovers arising from social interactions leads player 1 to behave as if she received a motivational impulse $\delta\gamma$ from player 2's phone call. While the phone call serves as a convenient analytical example, this is obviously true for any factor affecting either of the players' utilities. This interpretation of the equilibrium features of the two-person game thus fits the structure of a bivariate probit model that we define formally and estimate in Section 3.

Notice that, in this setting, the spillover parameter δ is a fraction of b, the additional payoff if both individuals donate. It can have many different interpretations, such as utility from spending time together, or a reduced transportation cost from joint travel. It could also be a social recognition utility or image utility experienced if the other member of the pair sees her partner donating. Irrespective of the mechanism, this induces behavior as if the individual were directly affected by the peer's propensity to donate.

Version 2: complete information about c_i.

In this version of the game, player 1 will donate if $c_1 < B$, and if he is certain that player 2 will also donate, he will donate also if $B < c_1 < B + b$. Similarly, player 2 will donate if $c_1 < B + \gamma$, and if she is certain that player 1 will also donate, she will donate also if $B + \gamma < c_1 < B + b + \gamma$. Overall, this implies that

$$\begin{aligned} p_1 &= \Pr(c_1 < B) + \Pr(B < c_1 < B + b) \cdot \Pr(c_2 < B + b + \gamma) \\ &= \frac{B}{C} + \frac{b}{C}\frac{B + b + \gamma}{C} = \frac{B}{C} + \delta\frac{B + b}{C} + \delta\frac{\gamma}{C} \end{aligned} \tag{A.4}$$

where the second line of the equation exploits the properties of the uniform distribution. Similarly, for player 2, we have

$$\begin{aligned} p_2 &= \Pr(c_2 < B + \gamma) + \Pr(B + \gamma < c_1 < B + b + \gamma) \cdot \Pr(c_1 < B + b) \\ &= \frac{B + \gamma}{C} + \frac{b}{C}\frac{B + b}{C} = \frac{B}{C} + \delta\frac{B + b}{C} + \frac{\gamma}{C} \end{aligned} \tag{A.5}$$

As can be seen from equations (A.4) and (A.5), the ratio of the impacts of γ on player 2 compared to player 1 again identifies the spillover effect $\delta \equiv b/C$, as in the case with incomplete information. Thus, in a game with complete information, the same behavioral pattern that leads to a policy multiplier emerges.

To understand the logic, it is useful to consider the example of, say, a husband and wife. Assume that the wife receives a phone call, which raises her benefit from donating. For a range of cost draws, this is not enough to induce her to donate alone. However for a range of cost draws for the husband $B < c_2 < B + b$, she knows that if she donates, her husband will donate too. If $B + \gamma < c_1 < B + \gamma + b$, this will make her net benefit positive (because it adds the payoff b) and tips her to donate blood. In turn, this also induces the husband to donate blood. Thus, the spillovers are present in this sequential example as well: the phone call to the wife induces the husband to donate. Moreover, the presence of the husband amplifies the effectiveness of the phone call on the wife's propensity to donate, just like in the simultaneous model.

As our analytical example above shows, averaging over the population of donors and all possible cost draws again leads individuals to behave as if motivation spilled over between donors. As it turns out, this produces exactly the same policy multiplier.

A.2 TSLS Estimation of the Spillovers Arising from Social Interactions

We apply the basic TSLS procedure to estimate spillovers arising from social interactions in a linear probability model (Moffitt 1999). In the first stage, we predict the peer's donation, $\hat{Y}_{2pt}$, using the instrumental variable, P_{2pt}, and all exogenous variables by estimating the following linear model[22]:

$$Y_{2pt} = \eta_0 + \eta_1 P_{2pt} + \eta_2 P_{1pt} + \eta_3 X_{2pt} + \eta_4 X_{1pt} + \epsilon_{2pt} \,. \tag{A.6}$$

In the second stage, we regress the other focal donor's decision to donate blood, Y_{1pt}, on the peer's predicted donation, $\hat{Y}_{2pt}$, and all exogenous variables:

$$Y_{1pt} = \phi_0 + \phi_1 P_{1pt} + \phi_2 X_{1pt} + \phi_3 X_{2pt} + \phi_4 \hat{Y}_{2pt} + \epsilon_{1pt} \,. \tag{A.7}$$

Table 9 reports the estimated second-stage coefficients for three different specifications. Column (1) shows the estimated coefficients without any fixed effects, column (2) includes location fixed effects, and column (3) additionally includes month fixed effects. In sum, the linear probability model yields qualitatively the same results as the bivariate probit model.

Donors who receive a phone call are about 10 percentage points more likely to donate blood than donors who do not receive such a phone call. As in the bivariate probit model, this effect is highly statistically significant and robust. The instrument easily passes the standard tests for strong instruments (Kleibergen and Paap (2006) F-statistics in the first stage: (1) 44.62, (2) 41.78, (3) 34.23). Thus, in terms of the effectiveness of the phone call, the TSLS estimates are virtually identical to the marginal effects obtained from our baseline specification.

We observe strong and significant spillovers arising from social interactions which are robust to fixed effects. A focal donor's probability to donate blood increases by about 47 percentage points if her peer donates. In this model, again, the social multiplier is given by $1/(1 - \phi_4)$. With a value of about 1.89, it is in line with the bivariate probit model.

The estimated influence of individual characteristics on donation rates is robust and comparable to the bivariate probit model too. Given a positive baseline donation rate of 32 percent, men are about 4 percentage points more likely to donate blood than women. This effect is statistically highly significant and robust. Donation rates increase with age. On average, a donor that is 10 years older donates 4 percentage points more often than the younger donor. Hence, in terms of magnitude, the influence of gender corresponds to an 10-year age effect. Furthermore, a regular donor is more likely to donate than an irregular or an inactive donor. Similar to the bivariate probit model, the effects of previous donations are much stronger than gender and age effects. This indicates that past unobservables strongly influence donor motivation. Blood types do not affect the donors' motivation (F-test for joint significance, p-values > 0.4 in all specifications). Individuals with highly demanded, negative blood types do not exhibit higher donation

[22]Results of the first stage regression are reported in table 8.

Table 8: Linear probability model (first stage regressions)

Binary dependent variable: peer's donation decision (0,1)			
OLS regression	(1)	(2)	(3)
Constant (η_0)	0.157***		
	(0.0117)		
Peer's phone call (η_1)	0.101***	0.0978***	0.0900***
	(0.0151)	(0.0151)	(0.0154)
Focal donor's phone call (η_2)	0.0468***	0.0440***	0.0362**
	(0.0146)	(0.0149)	(0.0151)
Peer's characteristics (η_3)			
Male	0.0405***	0.0372***	0.0373***
	(0.00795)	(0.00778)	(0.00779)
Age	0.00387***	0.00390***	0.00389***
	(0.000263)	(0.000258)	(0.000258)
# of donations in year before study			
1	0.167***	0.170***	0.175***
	(0.00760)	(0.00753)	(0.00759)
2	0.306***	0.321***	0.324***
	(0.0103)	(0.0103)	(0.0103)
3	0.386***	0.425***	0.428***
	(0.0207)	(0.0214)	(0.0213)
4	0.315***	0.360***	0.349***
	(0.0722)	(0.0666)	(0.0677)
Blood Types			
O-	0.00312	0.00378	0.00852
	(0.0176)	(0.0173)	(0.0174)
A+	-0.00842	-0.00706	-0.00714
	(0.00722)	(0.00702)	(0.00703)
A-	-0.00438	0.000602	0.00259
	(0.0130)	(0.0128)	(0.0129)
Focal donor's characteristics (η_4)			
Male	0.00787	0.00461	0.00470
	(0.00795)	(0.00776)	(0.00778)
Age	-0.000545**	-0.000508*	-0.000523**
	(0.000267)	(0.000262)	(0.000263)
# of donations in year before study			
1	-0.0109	-0.00771	-0.00294
	(0.00788)	(0.00777)	(0.00781)
2	-0.00364	0.0115	0.0145
	(0.0101)	(0.0101)	(0.0101)
3	-0.00794	0.0313	0.0339*
	(0.0203)	(0.0205)	(0.0206)
4	0.0276	0.0728	0.0620
	(0.106)	(0.0965)	(0.0976)
Blood Types			
O-	-0.0164	-0.0157	-0.0110
	(0.0161)	(0.0162)	(0.0163)
A+	0.000137	0.00149	0.00141

	(0.00729)	(0.00707)	(0.00708)
A-	-0.0257**	-0.0208	-0.0188
	(0.0128)	(0.0127)	(0.0127)
F-tests of instrument	44.62	41.78	34.23
174 Location FEs?	no	yes	yes
20 Month FEs?	no	no	yes
# of individual observations	26,842	26,842	26,842
# of pairs	5,053	5,053	5,053

Household cluster-robust standard errors in parentheses.

Levels of significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Age normalized to sample average.

rates (F-test for joint significance, p-values > 0.6 in all specifications).

Table 9 also shows some evidence that the peer's characteristics influence the focal donor's motivation to donate. Namely, increasing the peer's age by one year significantly decreases the probability to donate by 0.2 percentage points. Furthermore, the coefficients on the donation frequency in the year before the study reveal that donors living with irregular donors are more likely to donate than donors living with regular donors. In sum, we provide some evidence that focal donors also react to the peer's exogenous characteristics, besides her immediate motivation to donate. The fact that there are some significant relationships confirms that controlling for exogenous effects is crucial when attempting to identify the effect of spillovers arising from social interactions.

Table 9: Linear probability model (second stage regressions)

Binary dependent variable: donation decision (0,1)			
OLS regression	(1)	(2)	(3)
Phone call (ϕ_1)	0.0789***	0.0781***	0.0755***
	(0.0209)	(0.0205)	(0.0194)
Spillovers arising from social interactions (ϕ_4)	0.465***	0.449***	0.402**
	(0.150)	(0.155)	(0.168)
Constant	0.0842***		
	(0.0245)		
Focal donor's characteristics (ϕ_2)			
Male	0.0368***	0.0351***	0.0354***
	(0.00608)	(0.00600)	(0.00614)
Age	0.00412***	0.00413***	0.00410***
	(0.000297)	(0.000295)	(0.000292)
# of donations in year before study			
1	0.172***	0.173***	0.176***
	(0.00855)	(0.00845)	(0.00826)
2	0.307***	0.316***	0.318***
	(0.0112)	(0.0113)	(0.0113)
3	0.390***	0.411***	0.414***
	(0.0213)	(0.0220)	(0.0220)
4	0.302***	0.327***	0.324***
	(0.0424)	(0.0446)	(0.0458)
Blood Types			
O-	0.0107	0.0108	0.0129
	(0.0187)	(0.0184)	(0.0180)
A+	-0.00848	-0.00773	-0.00771
	(0.00692)	(0.00688)	(0.00683)
A-	0.00758	0.00993	0.0101
	(0.0136)	(0.0132)	(0.0130)
Peer's characteristics (ϕ_3)			
Male	-0.0109	-0.0121	-0.0103
	(0.00844)	(0.00822)	(0.00865)
Age	-0.00234***	-0.00226***	-0.00209***
	(0.000650)	(0.000672)	(0.000711)
# of donations in year before study			
1	-0.0884***	-0.0841***	-0.0731**
	(0.0264)	(0.0277)	(0.0304)
2	-0.146***	-0.133***	-0.116**
	(0.0470)	(0.0509)	(0.0552)
3	-0.187***	-0.160**	-0.138*
	(0.0618)	(0.0695)	(0.0748)
4	-0.119	-0.0890	-0.0783
	(0.0943)	(0.0952)	(0.0987)
Blood types			
O-	-0.0178	-0.0174	-0.0144
	(0.0166)	(0.0168)	(0.0172)
A+	0.00405	0.00466	0.00428

	(0.00716)	(0.00705)	(0.00702)
A-	-0.0237**	-0.0210*	-0.0198
	(0.0121)	(0.0123)	(0.0123)
F-statistics of instrument (1. Stage)	44.62	41.78	34.23
F-tests for joint significance (p-values)			
Focal donor:			
all blood types	0.48	0.47	0.43
negative blood types	0.80	0.72	0.66
non O-negative blood types	0.33	0.31	0.30
Peer:			
all characteristics	0.02	0.02	0.07
previous donations	0.02	0.02	0.09
all blood types	0.16	0.23	0.31
negative blood types	0.13	0.20	0.26
174 Location FEs?	no	yes	yes
20 Month FEs?	no	no	yes
# of individual observations	26,842	26,842	26,842
# of pairs	5,053	5,053	5,053

Household cluster-robust standard errors in parentheses.

Levels of significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Age normalized to sample average.

A.3 Testing for Behavioral Heterogeneity

To explore whether there is behavioral heterogeneity in the sense that there may exist distinct types of pairs that differ in the extent and type of social interaction, we estimate a finite mixture model.[23] As pointed out before, an estimated 48 percent of our donors are couples living together, and it is possible that social ties with regard to blood donations are stronger within couples than among other tenants. Moreover, prosocial behavior is known to be heterogeneous (e.g. Fischbacher, Gächter and Fehr (2001)), as there may exist several distinct social preference types (Breitmoser 2013; Iriberri and Rey-Biel 2013; Bruhin, Fehr and Schunk 2016; Bruhin et al. 2015). Thus, extending the pooled bivariate probit model to account for behavioral heterogeneity could yield important additional insights.

Estimation

The finite mixture model relaxes the assumption that there exists just one representative pair in the population. Instead, it allows the population to be made up by K distinct types of pairs differing in the extent of social interaction. The parameter vector θ_k is no

[23]Finite mixture models have become increasingly popular to uncover latent heterogeneity in various fields of behavioral economics. For recent examples, see Houser, Keane and McCabe (2004); Harrison and Rutström (2009); Bruhin, Fehr-Duda and Epper (2010); Conte, Hey and Moffat (2011); Breitmoser (2013); Bruhin et al. (2015).

longer representative of all pairs but rather depends on the type of the pairs as indicated by the subscript k. Thus, pair p's contribution to the likelihood of the finite mixture model,

$$\ell(\theta_k; P_p, X_p, Y_p) = \sum_{k=1}^{K} \pi_k \, f(\theta_k; P_p, X_p, Y_p)\,, \tag{A.8}$$

equals the sum over all K type-specific densities, $f(\theta_k; P_p, X_p, Y_p)$, weighted by the relative sizes of the corresponding types π_k. Since the finite mixture model makes no assumptions about how type-membership is related to observable characteristics, we do not know a priori to which type pair p belongs. Hence, the types' relative sizes, π_k, may be interpreted as ex-ante probabilities of type-membership, and the log likelihood of the finite mixture model is given by

$$\ln L(\Psi; P, X, Y) = \sum_{p} \ln \sum_{k=1}^{K} \pi_k \, f(\theta_k; P_p, X_p, Y_p)\,, \tag{A.9}$$

where the vector $\Psi = (\pi_1, \ldots, \pi_{K-1}, \theta_1', \ldots, \theta_K')'$ contains all parameters of the model.

Once we obtained the parameter estimates of the finite mixture model, $\hat{\Psi}$, we can classify each pair into the type it most likely belongs to. In particular, we apply Bayes' rule to calculate the pair's ex-post probabilities of type-membership given the parameter estimates of the finite mixture model,

$$\tau_{pk} = \frac{\hat{\pi}_k f(\hat{\theta}_k; P_p, X_p, Y_p)}{\sum_{m=1}^{K} \hat{\pi}_m f(\hat{\theta}_k; P_p, X_p, Y_p)}\,. \tag{A.10}$$

Note that the true number of distinct types in the population is unknown. Thus, a crucial part of estimating a finite mixture model is to determine the optimal number of distinct types, K^*, that the model accounts for. On the one hand, if K is too small, the model is not flexible enough to capture all the essential behavioral heterogeneity in the data. On the other hand, if K is too large, the finite mixture model overfits the data and captures random noise, resulting in an ambiguous classification of pairs into overlapping types. However, determining K^* is difficult for the following two reasons:

1. Due to the nonlinear form of the log likelihood (equation A.9), there exist no standard tests for K^* that exhibit a test statistic with a known distribution (McLachlan and Peel 2000). [24]
2. Standard model selection criteria, such as the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC), are not applicable either as they tend to favor models with too many types (Atkinson 1981; Geweke and Meese 1981;

[24] Lo, Mendell and Rubin (2001) proposed a statistical test (LMR-test) to select among finite mixture models with varying numbers of types, which is based on Vuong (1989)'s test for non-nested models. However, the LMR-test is unlikely to be suitable when the alternative model is a single-type model with strongly non-normal outcomes (Muthén 2003).

Table 10: *ICL-BIC* for determining the optimal number of types in a finite mixture model

	$K^{*}=1$	$K=2$	$K=3$
ICL-BIC	31,276.03	35,674.33	37,462.88
BIC	31,276.03	30,982.93	30,706.61
Entropy	0	4,691.4	6,756.27

Celeux and Soromenho 1996; Biernacki, Celeux and Govaert 2000*b*).

To determine the optimal number of distinct types, K^{*}, we approximate the Normalized Integrate Complete Likelihood (Biernacki, Celeux and Govaert 2000*a*) by applying the *ICL-BIC* criterion (McLachlan and Peel 2000),

$$ICL\text{-}BIC(K) = BIC(K) - 2\sum_{p}\sum_{k}\tau_{pk}\ln\tau_{pk}.$$

The *ICL-BIC* is based on the *BIC*, but additionally features an entropy term that acts as a penalty for an ambiguous classification of pairs into types. If the classification is clean, the K types are well segregated and almost all pairs exhibit ex-post probabilities of type-membership, τ_{k}, that are all either close to 0 or 1. In that case, the entropy term is almost 0 and the *ICL-BIC* nearly coincides with the *BIC*. However, if the classification is ambiguous, some of the K types overlap and many pairs exhibit ex-post probabilities of type-membership in the vicinity of $1/K$. In that case, the absolute value of the entropy term is large, indicating that the finite mixture model overfits the data and tries to identify types that do not exist. Thus, to determine the optimal number of types, we need to minimize the *ICL-BIC* with respect to K.

Results

The estimates of the finite mixture model provide no evidence for the existence of different types of pairs with distinct behavioral patterns. As shown in Table 10, the *ICL-BIC* reaches its lowest value for a model with $K^{*}=1$, i.e., one representative type. In particular, the ambiguity in the classification of pairs into types, as measured by the entropy in the *ICL-BIC*, is very large for models with more than one type. Hence, these models are overspecified and fit random noise rather than distinct types of pairs.

Figure 3 shows the distribution of the ex-post probabilities of type-membership, τ_{pk}, for a finite mixture model with $K=2$ types. It reveals that the classification of pairs into types is indeed highly ambiguous as the τ_{pk} of many pairs lie between 0 and 1. Thus, there is considerable overlap between the two types that the model tries to identify. As illustrated in Figure 4, the ambiguity in the pairs' classification into types becomes even more pronounced in the finite mixture model with $K=3$ types. Therefore, our results

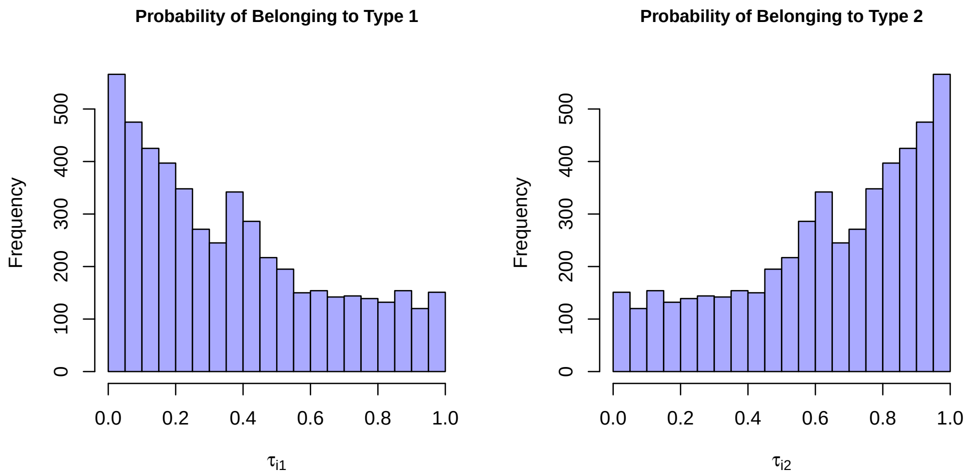

Figure 3: Ex-post probabilities of type-membership: model with $K = 2$ types

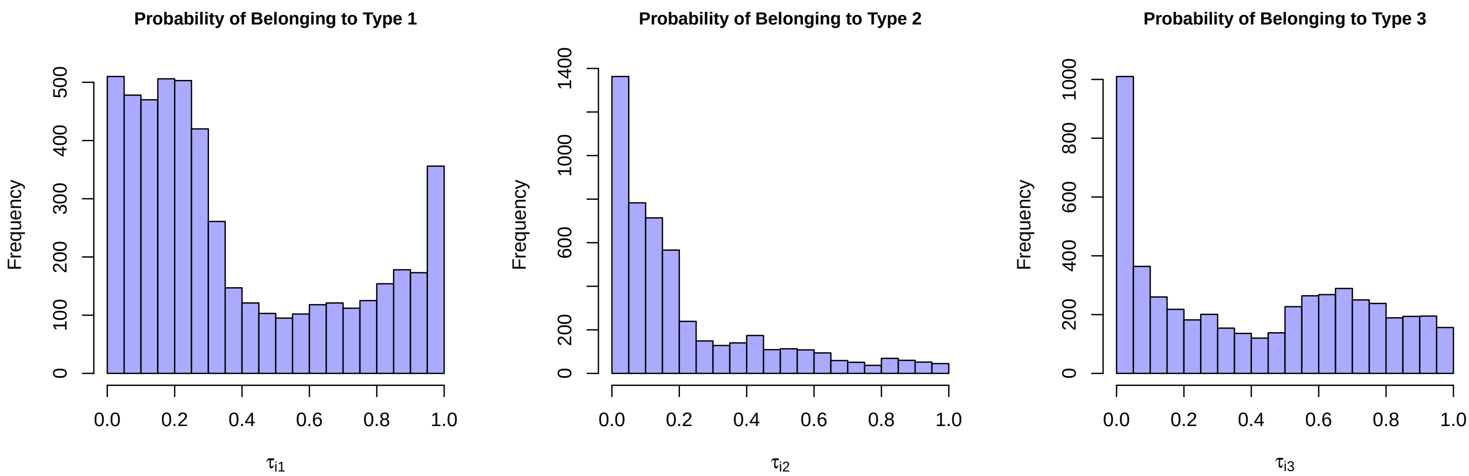

Figure 4: Ex-post probabilities of type-membership: model with $K = 3$ types

indicate that the baseline specification is a valid and parsimonious representation of the data. For completeness, we report the estimates for the finite mixture model with $K = 2$ types in Table 11.

Table 11: Finite mixture model with $K = 2$ types

Binary dependent variable: donation decision (0,1)		
Bivariate probit regression	Type 1 Individual	Type 2 Individual
Phone call (γ_k)	0.241	0.200*
	(0.196)	(0.111)
Spillovers arising from social interactions (δ_k)	0.495	0.355
	(0.449)	(0.440)
Constant (β_{0k})	-0.267	-1.079
	(0.284)	(0.777)
Focal donor's characteristics (β_{1k})		
Male	0.040	0.174***
	(0.076)	(0.052)
Age	0.021***	0.008**
	(0.006)	(0.003)
# of donations in year before study		
1	-0.321	1.154***
	(0.337)	(0.218)
2	0.955***	1.074***
	(0.241)	(0.158)
3	1.626***	1.159***
	(0.436)	(0.203)
4	0.904**	1.224***
	(0.415)	(0.221)
Blood Types		
O-	-0.141	0.185
	(0.423)	(0.216)
A+	0.130	-0.099*
	(0.100)	(0.054)
A-	0.238	-0.030
	(0.150)	(0.087)
Peer's characteristics (β_{2k})		
Male	-0.008	-0.052
	(0.092)	(0.083)
Age	-0.015	-0.001
	(0.012)	(0.003)
# of donations in year before study		
1	-0.059	-0.249
	(0.279)	(0.356)
2	-0.459	-0.330
	(0.447)	(0.484)
3	-0.958	-0.179
	(0.999)	(0.396)
4	-0.132	-0.575
	(0.586)	(0.530)
Blood Types		

O-	0.025	-0.097
	(0.182)	(0.086)
A+	-0.151**	0.099**
	(0.071)	(0.046)
A-	-0.225	-0.014
	(0.162)	(0.078)
ρ_k (correlation between errors in the structural form)	-0.582	-0.143
	(0.762)	(0.958)
π_k (share among the population)	0.366	0.634
	(0.107)	(0.107)
174 Location FEs?	yes	
20 Month FEs?	yes	
# of pair observations	13,421	
# of pairs	5,053	
Log likelihood	-14,369.93	

Household cluster-robust standard errors in parentheses.
Levels of significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$
Age normalized to sample average.

A.4 Recovering Parameters from the Reduced Form

Express equation 3.8 as

$$Y_{1p} = \alpha_0 + \alpha_1 P_{1p} + \alpha_2 P_{2p} + \alpha_3 X_{1p} + \alpha_4 X_{2p} + v_1 \tag{A.11}$$

Taking the ratio of the coefficients of P_{2p} and P_{1p} yields

$$\delta = \alpha_2/\alpha_1,$$

$$\gamma = \alpha_1(1 - \delta^2) = \alpha_1 - \alpha_2^2/\alpha_1.$$

δ has a direct interpretation as marginal effect because when dividing two reduced form coefficients, the density of the bivariate probit distribution cancels out. Once δ is identified, the other parameters can be derived too:

$$\beta_0 = \alpha_0(1 - \delta^2)/(1 + \delta) = \alpha_0(1 - (\alpha_2/\alpha_1)^2)/(1 + (\alpha_2/\alpha_1))$$

$$\beta_1 = \alpha_3 - \delta\alpha_4 = \alpha_3 - (\alpha_2/\alpha_1)\alpha_4$$

$$\beta_2 = \alpha_4 - \delta\alpha_3 = \alpha_4 - (\alpha_2/\alpha_1)\alpha_3$$

The standard errors of the structural form parameters are obtained via the delta-method:

$$\nabla(\delta) = \begin{pmatrix} -\alpha_2/\alpha_1^2 \\ 1/\alpha_1 \end{pmatrix}$$

$$\nabla(\gamma) = \begin{pmatrix} 1 + \alpha_2^2/\alpha_1^2 \\ -2\alpha_2/\alpha_1 \end{pmatrix}$$

$$\nabla(\beta_0) = \begin{pmatrix} \frac{1-\frac{{\alpha_2}^2}{{\alpha_1}^2}}{1+\frac{\alpha_2}{\alpha_1}} \\ \frac{2\alpha_0{\alpha_2}^2}{{\alpha_1}^3\left(1+\frac{\alpha_2}{\alpha_1}\right)} + \frac{\alpha_0\alpha_2\left(1-\frac{{\alpha_2}^2}{{\alpha_1}^2}\right)}{{\alpha_1}^2\left(1+\frac{\alpha_2}{\alpha_1}\right)^2} \\ -\frac{2\alpha_0\alpha_2}{{\alpha_1}^2\left(1+\frac{\alpha_2}{\alpha_1}\right)} - \frac{\alpha_0\left(1-\frac{{\alpha_2}^2}{{\alpha_1}^2}\right)}{\alpha_1\left(1+\frac{\alpha_2}{\alpha_1}\right)^2} \end{pmatrix}$$

$$\nabla(\beta_1) = \begin{pmatrix} \alpha_2\alpha_4/\alpha_1^2 \\ -\alpha_4/\alpha_1 \\ 1 \\ -\alpha_2/\alpha_1 \end{pmatrix}$$

$$\nabla(\beta_2) = \begin{pmatrix} \alpha_2\alpha_3/\alpha_1^2 \\ -\alpha_3/\alpha_1 \\ -\alpha_2/\alpha_1 \\ 1 \end{pmatrix}$$

$$se(\delta) = [\nabla(\delta)' \times Cov(\alpha_1, \alpha_2) \times \nabla(\delta)]^{1/2}$$

$$se(\gamma) = [\nabla(\gamma)' \times Cov(\alpha_1, \alpha_2) \times \nabla(\gamma)]^{1/2}$$

$$se(\beta_0) = [\nabla(\beta_0)' \times Cov(\alpha_0, \alpha_1, \alpha_2) \times \nabla(\beta_0)]^{1/2}$$

$$se(\beta_1) = [\nabla(\beta_1)' \times Cov(\alpha_1, \alpha_2, \alpha_3, \alpha_4) \times \nabla(\beta_1)]^{1/2}$$

$$se(\beta_2) = [\nabla(\beta_2)' \times Cov(\alpha_1, \alpha_2, \alpha_3, \alpha_4) \times \nabla(\beta_2)]^{1/2}$$

A.5 Marginal Effects in the Bivariate Probit Model

Define $Z_p = (P_p, Y_p^*, X_p),\ \zeta = (\gamma, \delta, \beta')'$. The discrete probability effect of the phone call holding the spillovers arising from social interactions constant is given by

$$\Delta P_{call} \equiv \Phi\left(\gamma_1 + \zeta'\overline{Z_p}\right) - \Phi\left(\zeta'\overline{Z_p}\right). \tag{A.12}$$

The change in the probability of donation of the focal donor receiving the phone call, and taking into account the feedback loops with the peer's motivation is given by

$$\Delta P_1 \equiv \Phi\left(\frac{\gamma_1}{1-\delta^2} + \zeta'\overline{Z_p}\right) - \Phi(\zeta'\overline{Z_p}), \tag{A.13}$$

where $1/(1-\delta^2)$ is the social amplification for the focal donor. Similarly, the effect on the peer not receiving a phone call is given by

$$\Delta P_2 \equiv \Phi\left(\frac{\gamma_1\delta}{1-\delta^2} + \zeta'\overline{Z_p}\right) - \Phi(\zeta'\overline{Z_p}), \tag{A.14}$$

where $\delta/(1-\delta^2)$ is the spillover onto the peer who has not received the phone call.

A.6 Bivariate Probit Model Without Correlation Between the Residuals

Table 12: Bivariate probit model with $\rho = 0$

Binary dependent variable: donation decision (0,1)			
Bivariate probit regression	(1)	(2)	(3)
Phone call (γ)	0.215***	0.220***	0.212***
	(0.061)	(0.061)	(0.059)
Spillovers arising from social interactions (δ)	0.489***	0.477***	0.434**
	(0.156)	(0.159)	(0.173)
Constant (β_0)	-0.512***	-0.674***	-0.659***
	(0.157)	(0.224)	(0.236)
Focal donor's characteristics (β_1)			
Male	0.116***	0.113***	0.115***
	(0.018)	(0.019)	(0.019)
Age	0.012***	0.012***	0.012***
	(0.001)	(0.001)	(0.001)
# of donations in year before study			
1	0.543***	0.562***	0.570***
	(0.028)	(0.028)	(0.028)
2	0.901***	0.953***	0.962***
	(0.033)	(0.035)	(0.035)
3	1.116***	1.206***	1.218***
	(0.059)	(0.063)	(0.063)
4	0.908***	1.004***	0.995***
	(0.111)	(0.125)	(0.126)
Blood types			
O-	0.037	0.036	0.045
	(0.055)	(0.055)	(0.054)
A+	-0.025	-0.023	-0.023

	(0.021)	(0.022)	(0.022)
A-	0.032	0.045	0.046
	(0.041)	(0.042)	(0.041)
Peer's characteristics (β_2)			
Male	-0.038	-0.044*	-0.038
	(0.027)	(0.026)	(0.028)
Age	-0.007***	-0.006***	-0.006***
	(0.002)	(0.002)	(0.002)
# donations in year before study			
1	-0.287***	-0.280***	-0.249**
	(0.087)	(0.092)	(0.102)
2	-0.452***	-0.428***	-0.382**
	(0.143)	(0.157)	(0.172)
3	-0.568***	-0.502**	-0.446**
	(0.182)	(0.209)	(0.227)
4	-0.417	-0.338	-0.308
	(0.301)	(0.309)	(0.320)
Blood Types			
O-	-0.057	-0.057	-0.049
	(0.050)	(0.051)	(0.053)
A+	0.011	0.012	0.011
	(0.022)	(0.022)	(0.022)
A-	-0.079**	-0.079**	-0.075*
	(0.038)	(0.040)	(0.040)
ρ (correlation between errors in the structural form)	0.000	0.000	0.000
Wald-tests for joint significance (p-values)			
Focal donor			
all blood types	0.42	0.38	0.35
negative blood types	0.69	0.57	0.55
non O-negative blood types	0.28	0.23	0.22
Peer:			
all characteristics	0.03	0.05	0.16
previous donations	0.03	0.02	0.12
all blood types	0.13	0.16	0.23
negative blood types	0.10	0.12	0.16
174 Location FEs?	no	yes	yes
20 Month FEs?	no	no	yes
# of pair observations	13,421	13,421	13,421
# of pairs	5,031	5,031	5,031
Log likelihood	-15,705.81	-15,247.68	-15,193.15

Household cluster-robust standard errors in parentheses.

Levels of significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Age normalized to sample average.