DISCUSSION PAPER SERIES

IZA

IZA DP No. 8738

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

Adrian Bruhin
Lorenz Goette
Simon Haenni
Lingqing Jiang

December 2014

Forschungsinstitut
zur Zukunft der Arbeit
Institute for the Study
of Labor

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

Adrian Bruhin
HEC Lausanne

Lorenz Goette
HEC Lausanne and IZA

Simon Haenni
HEC Lausanne

Lingqing Jiang
HEC Lausanne

Discussion Paper No. 8738
December 2014

IZA

P.O. Box 7240
53072 Bonn
Germany

Phone: +49-228-3894-0
Fax: +49-228-3894-180
E-mail: iza@iza.org

IZA Discussion Paper No. 8738
December 2014

ABSTRACT

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

Spillovers of prosocial motivation are crucial for the formation of social capital. They facilitate interactions among individuals and create social multipliers that amplify the effects of policy interventions. We conducted a large-scale intervention study among dyads of blood donors to investigate whether social ties lead to motivational spillovers in the decision to donate. The intervention is a randomized phone call making donors aware of a current shortage of their blood type and serving us as an instrument for identifying motivational spillovers. About 40% of a donor's motivation spills over to the other donor, creating a significant social multiplier of 1.78.

JEL Classification: D03, C31, C36

Keywords: social interaction, social ties, prosocial motivation, blood donation, bivariate probit

Corresponding author:

Lorenz Goette
University of Lausanne
Batiment Internef 536
1015 Lausanne
Switzerland
E-mail: lorenz.goette@unil.ch

1 Introduction

Social capital is thought to engender trust and cooperation between individuals, and to play a potentially important role in economic development (Knack and Keefer 1997; Putnam 2000; Durlauf 2002). Even though this concept eludes a precise definition, economists have converged on the view that spillovers of prosocial motivation spreading from one individual to another are crucial for the formation of social capital within a community. They provide a social fabric, or capital, that makes interactions between individuals easier and less prone to opportunistic exploitation (Bowles and Gintis 2002). For example, Putnam (2000) famously argued that the decline in civic activities in the US, that previously severed social ties between individuals in communities, caused a sharp reduction in prosocial behavior and hence social capital. Olken (2009) provided empirical support for this argument.

While many papers study indirect outcomes of social capital, few attempt to examine the underlying motivational spillovers. Laboratory experiments have demonstrated that individuals are more willing to contribute to public goods if others do so as well (Falk and Fischbacher 2002; Fehr and Fischbacher 2004). Evidence from field experiments shows that informing individuals about prosocial behavior of others increases the individuals' propensity to donate (Frey and Meier 2004; Shang and Croson 2009). These results are consistent with various different mechanisms: On the one hand, the experimental manipulations could lead to more prosocial behavior as they may be informative about the value of the good cause (Bénabou and Tirole 2003), or signal social norms (Bénabou and Tirole 2011). On the other hand, the increase in prosocial behavior could also reflect a genuine response to the other individuals' motivation. While each of these mechanisms has interesting policy implications, the last stands out since it generates a "social multiplier" that lies at the heart of social capital. If prosocial motivation spills over between individuals, any intervention that affects individual motivation will feed back into the community and will have a larger aggregate effect akin to the Keynesian consumption multiplier. Moreover, previous research suggests that such motivational spillovers may rely on social ties that strengthen altruism between individuals (Goette, Huffman and Meier 2006; Twenge et al. 2007; Leider et al. 2009, 2010).

In this paper, we investigate whether social ties lead to motivational spillovers for contributing to a public good with diffuse benefits to a large group. We test this hypothesis in the context of voluntary blood donations. Voluntary blood donations are a textbook example of prosocial behavior as donors receive no material compensation but bear the personal cost of giving their blood. Nevertheless, they provide for the majority of blood products used for medical treatments in the developed world (World Health Organization 2011).

We use data comprising the universe of more than 40,000 blood donors registered for blood drives by the Blood Transfusion Service of the Red Cross in Zurich, Switzerland (BTSRC). As social ties are fostered by closeness in space (Marmaros and Sacerdote 2006;

Goette, Huffman and Meier 2006) and age (Marsden 1988; McPherson, Smith-Lovin and Cook 2001; Kalmijn and Vermunt 2007), we focus on the 7,446 donors in our sample who live at an address with a fellow tenant who is also a donor in the same blood drive, and who is within less than 20 years difference in age. Over the sample period from April 2011 to January 2013, these donors are invited repeatedly to blood drives, creating 10,120 observations of dyads deciding whether or not to donate. An estimate 66 percent of them are cohabiting couples. Since social ties within these dyads are most likely, we can test if prosocial motivation spreads within them.

Identifying motivational spillovers is difficult (Manski 2000; Durlauf 2002): simply observing a correlation in behavior within dyads is not necessarily evidence of motivational spillovers. Both donors may be exposed to a similar environment, thus experiencing correlated shocks to their motivation that generate an omitted-variable bias which exaggerates the causal effect of motivational spillovers. Furthermore, the presence of motivational spillovers itself creates an endogeneity problem between the two individuals within a dyad. If motivation spills from one individual to her fellow tenant, that motivation (partly) spills back, causing an endogeneity bias also known as the reflection problem (Manski 1993).

In order to cut through these potential biases, one needs an instrument that affects a donor's motivation without directly impacting her fellow tenant. We use a phone call to a random subset of the invited donors two days before the blood drive, urging them to donate because their blood type is in short supply at the moment. Receiving such a phone call directly increases the recipient's motivation to give blood (Bruhin and Goette 2014), but leaves her fellow tenant's motivation unaffected, unless the donors within the dyad interact.

We apply the linear-in-means model by Manski (1993) in a bivariate probit specification. This allows us to empirically identify motivational spillovers using the randomized phone call as an instrument, without imposing restrictive assumptions on how contextual effects affect donations. Furthermore, it enables us to distinguish motivational spillovers from so-called exogenous social interaction effects. With motivational spillovers, a donor's motivation to give blood is affected by her fellow tenant's motivation, whereas under exogenous social interaction, it is influenced by the fellow tenant's characteristics. The distinction between these two types of social interaction is policy relevant. As motivational spillovers go in both directions and result in a feedback loop between the individuals, they create a "social multiplier" that could greatly amplify the effectiveness of policy interventions. Exogenous social interaction, on the other hand, goes just in one direction and does not create any social multipliers.

We find strong evidence for motivational spillovers: our estimates imply that 40 percent of a fellow tenant's motivation spills over to one's own motivation to donate. These spillovers generate a significant social multiplier of 1.78: i.e., any intervention that increases an individual's propensity to donate by, say, 10 percent leads to an aggregate increase in donation rates by almost 18 percent. By contrast, we find no evidence that a fellow tenant's characteristics, such as age, gender or previous donation history affects one's donation decision apart from their direct effect on the fellow tenant's motivation.

An important concern in our context is that it is not the donor's motivation that is transmitted, but rather the information about the scarcity of a specific blood type that the phone call conveys. However, we are able to check the validity of the exclusion restriction of our instrument in two ways. First, we examine whether a phone call to a fellow tenant with a different blood type also affects one's probability to donate. If it were only the information about the temporary shortage of a specific blood type that was transmitted, the effect should be absent for fellow tenants with a different blood type, or at least significantly weaker. However, we find the same effect as for fellow tenants with the same blood type. Furthermore, we can check if a phone call to a fellow tenant is ineffective if the donor himself also was called by the BTSRC. Again, if only the information mattered, we would expect the effect to be weaker if both members of a dyad received a phone call, but we find no evidence thereof. While, ultimately, exclusion restrictions always remain untestable, our two validity checks rule out an important class of alternative explanations for our findings.

We also explore the role of the nonlinearity in our estimation results by reestimating our model by two-stage least squares (TSLS). Although the models differ slightly in their interpretation, we also find significant spillover effects in the TSLS specification, and virtually the same implied social multiplier.

An interesting question is whether our results are driven by the subset of roughly 66 percent of cohabitating (opposite-sex) couples in our data. The panel structure of our data and the modeling of the donors' decisions within a bivariate probit model lends itself to a straightforward analysis of heterogeneity of this sort with a finite mixture model. When we search the data for heterogeneity of this sort, we find no evidence of distinct types of dyads. Since a finite mixture model with more than one type of dyads overfits the data, it seems that motivational spillovers, in the case of blood donations, are equally present in cohabiting couples as well as among fellow tenants.

Overall, our study provides strong support for the notion that prosocial motivation directed at third parties can spill over between individuals with social ties. Thus, these spillovers are not confined to solely motivations benefiting the individual with whom the ties exist. These motivational spillovers alter the cost-benefit calculations of a behavioral intervention in important ways: with our estimated spillover of 40 percent onto the fellow tenant, they magnify the change in motivation due to the phone call by $1/(1-0.4^2)$ for the individual called, and raise motivation by a fraction $0.4/(1-0.4^2)$ of its original impact. Overall, the resulting social multiplier of $1/(1-0.4) = 1.78$ nearly doubles the effectiveness of the behavioral intervention. Consequently, this affects optimal policy, as the behavioral intervention has substantially higher benefits when targeted towards dyads instead of isolated individuals.

This study also contributes to the existing empirical literature on voluntary blood donation. Most of this literature focuses on the direct effects of policy interventions on donor motivation (for examples see Goette and Stutzer (2008); Goette et al. (2009); Lacetera and Macis (2012b); Niessen-Ruenzi, Weber and Becker (2014)). However our study shows that any such intervention may also affect donors that were assigned as controls in these studies, thus possibly underestimating the treatment effects. This bias can be substantial: assuming the worst case scenario that one donor in a dyad is in the treated group and the other is in the control, the estimated treatment effect will be attenuated by a factor of $1/(1 + 0.44) \approx 0.7$. [1]

Furthermore, the present study also adds to the broader literature on social interaction that highlights the importance of social multipliers in various contexts. For example, Cipollone and Rosolia (2007) find strong social interaction 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 Dorani (2014) 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 data set, how we isolate dyads of donors with potential social ties, and the phone call we use as the instrument for identifying motivational spillovers. Section 3 presents the econometric analysis. Section 4 discusses the results and presents some robustness checks. Finally, section 5 concludes.

2 Data Set

This section discusses the origin and structure of the panel data set, how we isolate dyads of donors with potential social ties, and the instrument for identifying the motivational spillovers.

[1] Lacetera, Macis and Slonim (2014) studied indirect effects of interventions of a different type: they find in a randomized field experiment that incentive offers made to some donors also increase donation rates of other donors. However, this spillover effect is partially explained by a spatial displacement effect, i.e. a substantial number of donors shifts from blood drives without incentives to neighboring blood drives that offer incentives.

2.1 Origin and Structure

The panel data set originates form the BTSRC and contains information about all blood drives that took place in the canton of Zurich between April 2011 to January 2013.[2] The blood drives were coordinated by local organizations, such as local church chapters or sports clubs, but organized centrally by the BTSRC which administers the invitation of donors and provides the equipment and personnel to take blood. For each upcoming blood drive, the BTSRC sends a personalized invitation letter to all eligible donors registered in its data base, i.e. donors who did not give blood within the past three months and fulfill all donation criteria. Two days before the blood drive takes place, all invited donors additionally receive a text message reminding them about the time and location of the blood drive. These invitations constitute the observations in the panel data set, as each of them requires the individuals to decide whether to donate or not. In total we observe over 40,000 registered donors. On average, each registered donor received 3 invitations, resulting in over 120,000 observations.

For each observation, the data set contains the following information: a binary indicator whether the donor gave blood at the blood drive she was invited to, the donor's street, 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 beginning of 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.

2.2 Identifying potential social ties

To test for motivational spillovers, we aim to focus on individuals with strong social ties. However, in our data set, we only observe a limited set of the donors' characteristics. Thus, we draw on earlier evidence that shows that proximity is an important predictor of social ties. Marmaros and Sacerdote (2006) show that random allocations to university dorms are strong predictors of subsequent friendships. Similarly, Goette, Huffman and Meier (2006) find that random allocations to platoons in a training unit in the Swiss Army immediately lead to strong social ties between individuals. Secondly, we draw on evidence that friends are often very close in age: several studies document that friendship pairs have very small age differences, with roughly 90 percent of the friendship pairs having an age difference of less than 20 years (Marsden 1988; McPherson, Smith-Lovin and Cook 2001; Kalmijn and Vermunt 2007).

In this spirit, we define groups of fellow tenants, registered for the same blood drive, by exploiting the available information on the donors' place of residence. Note, however, that

[2] Blood drives are special events where donors come to give blood. In addition, there are also fixed donation centers that collect about 50% of all whole blood transfusions. However, we exclude data from these fixed donation centers as they do not conduct any randomized interventions.

for reasons of data protection, we only observe the donors' addresses but not whether they live in the same household.

We restrict attention to pairs of donors, i.e. dyads. We focus on such dyads for the following two reasons. First, by eliminating large groups of fellow tenants, we increase the probability that two donors interact with each other. With a third donor present, it is more likely that donors are not friends with each other. Second, by focussing on dyads, we can use a bivariate probit model that is frequently used for estimating the effect of an endogenous binary regressor on a binary outcome variable (Abadie 2000; Angrist 2001; Winkelmann 2012). Applying this first restriction yields 5,053 distinct dyads with 13,421 observations at the dyad-level, or $2 \times 13,421 = 26,842$ observations at the donor-level. The second restriction limits the age difference between the two donors within each dyad to less than 20 years, motivated by the studies cited earlier. This reduces our sample further to $3,723$ dyads with $10,120$ observations at the dyad level.

Table 1 reports descriptive statistics of the sample we use for estimation. The average age of our donors is 43 years, and 51 percent of the donors are male. It is noteworthy that roughly 83 percent of the dyads are mixed-gender, far more than one would expect under random sampling. This allows us to get a sense of what fraction of blood donors are cohabitating (heterosexual) blood donors, assuming that for non-cohabiting tenants, the gender composition is random. Simple calculations show that the fraction of cohabiting couples is roughly 66 percent.[3] [4] Thus, our sample contains a large group of cohabiting couples, but about one-third is not. This raises the question of whether the social ties might be weaker for the latter group than for the former. In section 3.3, we will address this question explicitly by formally examining heterogeneity in our sample.

Table 2 illustrates the distribution of donations within dyads. It shows that 18.4% of all dyads exhibit two donations upon both being invited, 27.6% show one donation, and 54% have no donations. Note that there are significantly more dyads with either both donors or no donor giving blood than expected under independence (χ^2-test for independent donations within dyads, p-value ≤ 0.001). Thus, donations within dyads are positively correlated. We are going to analyze this positive correlation in greater detail to determine the extent to which it is due to motivational spillovers.

2.3 Instrument for Identifying the Effects of Social Interaction

As mentioned in the introduction, the BTSRC uses phone calls to invited donors to increase turnout for blood types that are in particularly short supply. These phone calls are highly effective, raising donation rates by roughly 8 percentage points from the baseline

[3]Denote by x the fraction of cohabiting couples. Under random matching for non-cohabiting couples, x is given by $x + (1 - x) \cdot 0.5 = 0.83$, which yields $x = 0.66$.

[4]The BTSRC does not allow blood donations from homosexual individuals, thus ruling out same-sex couples.

Table 1: Descriptive statistics for dyads (intra-dyad age difference < 20 years)

Variable	Mean	Std. Dev.	Corr. in dyad
Donation	0.322	0.467	0.368
Phone call	0.089	0.285	0.075
Age	43.186	11.850	0.859
Male	0.511	0.500	mixed-gender dyads: 83%
# of observations	10,120		
# of dyads	3,723		

Table 2: Distribution of donations within dyads

Dyad	Both donate (1,1)	One donates (1,0) & (0,1)	Nobody donates (0,0)
Empirical distribution:	18.40%	27.60%	54.00%
Distribution under independence:	10.37%	43.66%	45.97%
χ^2-test for independent donations within dyads: $p < 0.001$			

of 30 percentage points (Bruhin and Goette 2014). Therefore, the intervention satisfies the criterion that it affects the donor's motivation. In order to be a valid instrument, we also need to assert that the phone call itself does not affect the fellow tenant's motivation directly, i.e. that it satisfies the exclusion restriction. In part, this is guaranteed by the institutional setup. The BTSRC reaches the registered donors during office hours on their mobile phones. Each phone call provides the same information about the upcoming blood drive, stating explicitly: "Your blood type X is in short supply, please come and donate at the upcoming blood drive." Since the phone call reaches the recipient during office hours on her mobile phone, it does not directly affect the motivation of the fellow tenant who is most likely not present at that time. Moreover we are going to present two validity checks in subsection 4.2 that address these issues more explicitly.

Table 3 verifies that, conditional on blood types, the phone calls are barely correlated with other individual characteristics. The correlation of the phone calls with gender is not significant. Their correlation with age is statistically significant but very small in magnitude. For example, the probability of receiving a phone call decreases by only 0.1 percentage points for every additional 10 years of age. The phone calls also show no clear correlation pattern with the donation history in the year prior to the onset of the study. In fact, the corresponding coefficients are jointly significant in specification (1), without fixed effects, and specification (2), with fixed effects for the location of the blood drives (location fixed

Table 3: Randomization checks for phone calls

Binary dependent variable: Received a phone call			
OLS Regression	(1)	(2)	(3)
Male	-0.002	-0.002	-0.002
	(0.01)	(0.001)	(0.001)
Age	-0.0001**	-0.0001**	-0.0001**
	(0.000)	(0.000)	(0.000)
# of donations in year before study†			
1	-0.004***	-0.005***	-0.002*
	(0.001)	(0.001)	(0.001)
2	-0.004**	-0.005***	-0.003**
	(0.002)	(0.002)	(0.002)
3	0.001	-0.003	-0.002
	(0.004)	(0.003)	(0.003)
4	0.003	0.004	0.008
	(0.014)	(0.013)	(0.013)
5	-0.011***	0.008	0.009
	(0.003)	(0.012)	(0.010)
Blood Types			
O-	0.724***	0.723***	0.725***
	(0.004)	(0.004)	(0.004)
A+	-0.012***	-0.013***	-0.013***
	(0.000)	(0.001)	(0.001)
A-	0.252***	0.252***	0.251***
	(0.004)	(0.004)	(0.004)
Constant	0.020***	-0.038***	0.100*
	(0.002)	(0.002)	(0.004)
† F-test for joint significance of donation history dummies (p-value)	0.001	0.002	0.22
Location FEs?	no	yes	yes
Month FEs?	no	no	yes
# of observations	125,692	125,692	125,692
R-squared	0.541	0.558	0.568

Individual cluster robust standard errors in parentheses.

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

effects). But they are jointly insignificant in specification (3), with both location and month fixed effects (F-tests for joint significance (1) p-value: 0.001, (2) p-value: 0.002, (3) p-value: 0.225). Note that the correlations in specification (1) and (2) between the phone calls and the donation history result by construction, because new donors entered the data set while the study was ongoing. These new donors' donation history was necessarily zero at the time they received their first phone call. Because the month fixed effects pick up the resulting correlations, they are jointly insignificant in specification (3). Finally, the phone calls are strongly correlated with blood types. Their incidence is higher for negative blood types which can be used more flexibly. The BTSRC especially favors blood type O-negative which is universally compatible with any other blood type.

3 Econometric Analysis

This section presents the econometric analysis for identifying motivational spillovers. It first introduces the structural model and formally discusses the identification strategy. Subsequently, it briefly outlines the estimation procedure and our approach for dealing with potential behavioral heterogeneity.

3.1 Structural Model

The structural model is based on the linear-in-means model by Manski (1993). The motivation of donor i in dyad d to give blood is

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

For notational convenience we drop the subscript t for the invitation to an upcoming blood drive in this subsection. β_0 is a constant, measuring baseline motivation. Y^*_{-id} indicates the motivation of i's fellow tenant. Thus, the parameter δ captures the extent to which donor motivation spills over within dyads. X_{id} represents donor i's individual characteristics, including gender, age, blood type, and dummies for the number of donations in the year before the study began. X_{-id} are the same individual characteristics of i's fellow tenant. Hence, the parameter vector β_2 measures the effects of exogenous social interaction.

Since the decision whether or not to donate, Y_{id}, is binary and we study dyads of donors, we can estimate a bivariate probit model to capture the simultaneous decision-making of the two fellow tenants in each dyad.

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

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

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

We assume the error terms ϵ_{1d} and ϵ_{2d} to be bivariate normally distributed, with $\mathrm{E}(\epsilon_{1d}) = \mathrm{E}(\epsilon_{2d}) = 0$, $\mathrm{Var}(\epsilon_{1d}) = \mathrm{Var}(\epsilon_{2d}) = 1$, and $\mathrm{Cor}(\epsilon_{1d}, \epsilon_{2d}) = \rho$. The correlation between the random errors, ρ, captures both 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,

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

and the analogous expression for the fellow tenant:

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

The equations highlight the identification problem of motivational spillovers: we have three independent variables (the constant, X_{1d}, and X_{2d}), but four unknown parameters β_0, β_1, β_2, and δ. If we assumed that $\rho = 0$, then the functional form induced by the normality assumption over the residuals ϵ_{1d} and ϵ_{2d} would allow us to identify δ. To see why this is true, note that the error terms in (3.4) and (3.5) are linear combinations of the structural residuals ϵ_{1d} and ϵ_{2d}. Thus, when $\rho = 0$, one can identify δ off the correlation of these residuals. However, when $\rho \neq 0$, this in itself introduces a correlation in the residuals, leaving δ unidentified. In our context, ρ could reflect omitted exogenous effects or unobservable common shocks to the motivation stemming from similar environments, thus making identification suspect if one imposed $\rho = 0$.

This identification problem can be resolved by introducing the phone calls to the donors discussed in section 2.3. Within our model, they take on the role akin to an instrument in a TSLS estimation. Denote by P_{id} the binary variable indicating whether donor i in dyad d has received a phone call for the current invitation. As we argued above, a critical feature of this phone call is that it directly affects donor i's motivation, but not that of the fellow tenant. The econometric model then becomes

$$
\begin{aligned}
Y_{1d}^* &= \beta_0 + \gamma P_{1d} + \delta Y_{2d}^* + \beta_2' X_{1d} + \beta_2' X_{2d} + \epsilon_{1d} && (3.6) \\
Y_{2d}^* &= \beta_0 + \gamma P_{2d} + \delta Y_{1d}^* + \beta_1' X_{2d} + \beta_2' X_{1d} + \epsilon_{2d} && (3.7)
\end{aligned}
$$

Substituting equation 3.7 into 3.6 yields the following reduced form:

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

Note that the impact of the phone call P_{1d} on donor 1's motivation is given by $\frac{\gamma}{1-\delta^2}$ because of the motivational spillovers that go back and forth between the two fellow tenants (and amplify the response to the phone call if $0 < \delta < 1$). Its impact on donor 2, $\delta\frac{\gamma}{1-\delta^2}$, is different though, as only a fraction δ of the motivation spills over to donor 2 (and because the phone call has no direct impact on donor 2). This allows us to identify the parameter δ for motivational spillovers by dividing the reduced-form coefficient of donor 2's phone call by the reduced-form coefficient of donor 1's phone call.

Having obtained δ, we can identify all remaining structural parameters: as is obvious from the reduced form above, all other parameters are uniquely identified once δ is recovered, and we can use standard methods to calculate their standard errors.[5]

3.2 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. Dyad d's contribution to the model's density is

$$f(\theta; P_d, X_d, Y_d) = \prod_{t=1}^{T_d} \Phi_2 \left(w_{1dt}, w_{2dt}, \rho_{dt}^{*}\right) , \tag{3.9}$$

where $w_{idt} = q_{idt}Y_{idt}^{*}$, $q_{idt} = 2Y_{idt} - 1$, $\rho_{ht}^{*} = q_{1dt}q_{2dt}\rho_{dt}$, 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,

$$\ln L(\theta; P_d, X_d, Y_d) = \sum_{d=1}^{D} \ln f(\theta; P_d, X_d, Y_d) \, . \tag{3.10}$$

As the T_d observations of dyad d may be serially correlated, we estimate dyad 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.

[5] For details on how to recover the structural parameters and calculate standard errors, see section A.1 in the appendix

3.3 Testing for Behavioral Heterogeneity

In order to explore whether there is behavioral heterogeneity in the sense that there may exist distinct types of dyads that differ in the extent and type of social interaction, we estimate a finite mixture model[6]. As pointed out before, an estimated 66 percent of our donors are cohabiting couples, and it is possible that social ties with regard to blood donations are stronger within cohabiting couples than between the remaining fellow 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 2014; Bruhin and Goette 2014). Thus, extending the pooled bivariate probit model to account for behavioral heterogeneity could yield important additional insights.

The finite mixture model relaxes the assumption that there exists just one representative dyad in the population. Instead, it allows the population to be made up by K distinct types of dyads differing in the extent of social interaction. Consequently, the parameter vector θ_k is no longer representative for all dyads but rather depends on the type of the dyads as indicated by the subscript k. Thus, dyad d's contribution to the likelihood of the finite mixture model,

$$\ell(\theta_k; P_d, X_d, Y_d) = \sum_{k=1}^{K} \pi_k \, f(\theta_k; P_d, X_d, Y_d) \,, \tag{3.11}$$

equals the sum over all K type-specific densities, $f(\theta_k; P_d, X_d, Y_d)$, weighted by the relative sizes of the corresponding types π_k. Since we do not know a priori to which type dyad d belongs, the types' relative sizes, π_k, may be interpreted as ex-ante probabilities of type-membership. Hence, the log likelihood of the finite mixture model is given by

$$\ln L(\Psi; P, X, Y) = \sum_{d=1}^{D} \ln \sum_{k=1}^{K} \pi_k \, f(\theta_k; P_d, X_d, Y_d) \,, \tag{3.12}$$

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 dyad into the type it most likely belongs to. In particular, we apply Bayes' rule to calculate the dyad's ex-post probabilities of type-membership given the parameter estimates of the finite mixture model,

$$\tau_{dk} = \frac{\hat{\pi}_k f(\hat{\theta}_k; P_d, X_d, Y_d)}{\sum_{m=1}^{K} \hat{\pi}_m f(\hat{\theta}_k; P_d, X_d, Y_d)} \,. \tag{3.13}$$

Note that the true number of distinct types in the population is unknown. Thus, a

[6]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 and Goette (2014)).

crucial part of estimating a finite mixture model is to determine the optimal number of distinct types, K^*, 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 dyads into overlapping types. However, determining K^* is difficult for the following two reasons:

1. Due to the nonlinear form of the log likelihood (equation 3.12), there exist no standard tests for K^* that exhibit a test statistic with a known distribution (McLachlan and Peel 2000). [7]
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; 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),

$$ICL\text{-}BIC(K) = BIC(K) - 2\sum_{d=1}^{D}\sum_{k=1}^{K}\tau_{dk}\ \ln\tau_{dk}.$$

The *ICL-BIC* is based on the *BIC*, but additionally features an entropy term that acts as a penalty for an ambiguous classification of dyads into types. If the classification is clean, the K types are well segregated and almost all dyads exhibit ex-post probabilities of type-membership, τ_{dk}, 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 dyads 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 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.

4 Results

This section presents the results of the econometric analysis of the effects of motivational spillovers on donor motivation. First, it discusses the estimated coefficients of the bivariate probit model in our baseline specification. It then proceeds with two validity checks on

[7] 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).

the instruments to rule out that the mechanism is information passed on between donors, rather than motivation. Subsequently, it shows the finite mixture estimation that allows us to search for behavioral heterogeneity. We also reestimate the baseline specification using TSLS in order to minimize the role of functional-form assumptions in our estimates. Finally, we examine the robustness of our result with respect to the age restrictions that we impose on the dyads.

4.1 Main Results

Table 4 shows the estimated coefficients for the structural equation of three different specifications of the bivariate probit model. 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. Location fixed effects absorb differences between urban and rural areas as well as among the local organizers of the blood drives. Month fixed effects pick up seasonal fluctuations or special events that influence donor motivation, such as school holidays.

The results show that the phone call has a large and significant effect on the probability to donate. The coefficient γ is positive, and estimated with considerable precision, with a z-statistic of well over 3. Its absolute magnitude is not directly interpretable, as it reflects the impact of the phone call on the donor's motivation, Y^*, and not directly on the probability to donate. In order to express the effect on the probability to donate, we have to calculate its marginal probability effect as defined in equation (A.2) in the appendix. These calculations reveal that the probability to donate increases by 9 percentage points upon receiving a phone call, a sizable increase over the baseline donation rate of 32 percent. This estimate is virtually identical to the effect found in Bruhin and Goette (2014), who estimate the impact of the phone call on turnout in the entire population of blood donors, most of whom do not have a fellow tenant registered as a donor. Thus, focusing on dyads does not induce selectivity in terms of how strongly individuals react to the phone call.

Turning to our main interest, the parameter δ for motivational spillovers is significant in all three specifications, and hovering around 0.4. This implies that of a one-unit increase in the fellow tenant's motivation to donate roughly 40 percent spills over to the other donor in the dyad. That a donor's motivation to give blood strongly depends on her fellow tenant's motivation. This spillover generates a substantial "social multiplier" for any intervention. In our calculations for the effectiveness of the phone call above, we deliberate shut out the motivational spillovers between fellow tenants. To see how the phone call affects both donors, consider how the phone call to donor 1 changes her motivation to give blood Y_1^*:

its effect depends both on the phone call, and on the feedback induced by her fellow tenant, donor 2. Thus, $\Delta Y_1^* = \gamma + \delta \Delta Y_2^*$. Similarly, the fellow tenant is affect indirectly and her motivation 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 multiplier is $1/(1-\delta^2)$ for the individual receiving the call, and a fraction δ of that for the fellow tenant.

Our baseline estimate of $\delta = 0.44$ implies a substantial social multiplier, since $1/(1 - 0.44^2) = 1.24$ for donor 1 and $0.44/(1 - 0.44^2) = 0.54$ for her fellow tenant, donor 2. When calculating the marginal effect of a phone call taking into account these feedback effects (detailed in equations (A.3) and (A.4)), we find that the increase in the probability of donating for donor 1 is 12 percentage points, and that the increase in the probability to donate for donor 2 is roughly 5 percentage points after donor 1 received a phone call. Thus, motivational spillovers substantially increase the BTSRC's return to a phone call: it produces an aggregate 17 percentage higher donation rather than the 9 percentage points without motivational spillovers.

Individual characteristics matter for donor motivation as well. Male donors are significantly more likely to give blood than female donors. This gender effect is robust and quantitatively important. In terms of magnitude, the male dummy corresponds approximately to a ten-year difference in age. Donation rates also increase significantly with age. 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 donations in the year before entering the study predicts blood donations: the coefficients for the number of donations made prior to the beginning of the study reveal that regular donors are more likely to donate than irregular donors. Finally, blood types have no significant effect on donor motivation (Wald-test for joint significance of all blood types, $p > 0.4$ in all cases). In particular, donors with highly demanded, negative blood types do not donate more frequently (Wald-test for joint significance of negative blood types, $p > 0.6$ in all cases).

We find only weak evidence of exogenous social interactions, i.e. an impact of one fellow tenant's characteristic on the donation decision of the other, holding Y_{-1}^* constant. In general, the corresponding individual characteristics have small coefficients, and most of them are not individually significant. A joint F-test also reveals considerable fragility: adding location and month fixed effects knocks the F-statistics below the conventional levels of significance.

The estimates of ρ are between -0.2 and -0.3, depending on the specification, and are estimated with very little precision: in each of the specifications, the standard error is roughly 0.4. These imprecise estimates leave a rather large confidence band, thus highlighting again the advantage of not relying on assumptions about ρ to identify our parameter of interest δ.

Table 4: Bivariate probit model

Binary dependent variable: donation decision (0,1)			
Bivariate probit regression	(1)	(2)	(3)
Phone call (γ)	0.236***	0.241***	0.233***
	(0.063)	(0.066)	(0.061)
Endogenous Social Interaction (δ)	0.440***	0.443***	0.386**
	(0.165)	(0.169)	(0.183)
Constant (β_0)	-0.562***	-0.642***	-0.643***
	(0.168)	(0.213)	(0.238)
Donor's characteristics (β_1)			
Male	0.111***	0.100***	0.104***
	(0.024)	(0.024)	(0.025)
Age	0.012***	0.013***	0.013***
	(0.002)	(0.002)	(0.002)
# of donations in year before study (shares)			
1	0.498***	0.518***	0.527***
	(0.030)	(0.031)	(0.031)
2	0.843***	0.897***	0.908***
	(0.037)	(0.039)	(0.039)
3	1.012***	1.102***	1.118***
	(0.065)	(0.072)	(0.073)
4	1.000***	1.137***	1.118***
	(0.146)	(0.149)	(0.179)
Blood Types			
O-	0.037	0.033	0.042
	(0.058)	(0.061)	(0.059)
A+	-0.028	-0.023	-0.024
	(0.023)	(0.024)	0.024)
A-	-0.012	0.009	0.008
	(0.048)	(0.047)	(0.047)
Fellow tenant's characteristics (β_2)			
Male	-0.006	-0.018	-0.010
	(0.031)	(0.030)	(0.032)
Age	-0.006**	-0.006**	-0.006*

	(0.003)	(0.003)	(0.003)
# donations in year before study (shares)			
1	-0.228***	-0.237***	-0.200**
	(0.087)	(0.092)	(0.101)
2	-0.363**	-0.358**	-0.302*
	(0.144)	(0.159)	(0.173)
3	-0.414**	-0.372*	-0.304
	(0.184)	(0.210)	(0.227)
4	-0.616**	-0.521*	-0.498*
	(0.246)	(0.277)	(0.300)
Blood Types			
O-	-0.039	-0.047	-0.035
	(0.056)	(0.057)	(0.059)
A+	0.006	0.010	0.008
	(0.024)	(0.024)	(0.024)
A-	-0.089**	-0.078*	-0.075*
	(0.040)	(0.042)	(0.043)
ρ (correlation between residuals)	-0.275	-0.321	-0.198
	(0.380)	(0.377)	(0.413)
Wald-tests for joint significance (p-value)			
Donor:			
all blood types	0.49	0.69	0.61
negative blood types	0.66	0.86	0.76
non O-negative blood types	0.49	0.67	0.61
Fellow tenant:			
all characteristics	0.02	0.12	0.24
previous donations	0.08	0.05	0.17
all blood types	0.13	0.24	0.31
negative blood types	0.08	0.17	0.21
Location FEs?	no	yes	yes
Month FEs?	no	no	yes
# of observations	10,120	10,120	10,120
# of dyads	3,723	3,723	3,723
Log likelihood	-11,202.87	-10,917.67	-10,883.35

Household cluster robust standard errors in parentheses.

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

Age normalized to sample average.

4.2 Validity Checks on the Instruments

The crucial identifying assumption for the validity of our identification strategy is that only one's own phone call has a direct impact on one's own motivation, and not the fellow tenant's phone call directly. As we argued before, in terms of who is answering the phone call, this is a plausible assumption, as the phone calls are made to cell phones during office hours.

However, one could argue that it is not only the fellow tenant's motivation that may spill over, but also the information the fellow tenant received with this phone call. While ultimately, the identifying assumption remains just that, an assumption, our setup allows us to rule out two plausible sorts of such informational spillovers.

Our first test relies on differences in blood types within dyads. Recall that the phone call is made as a function of the scarcity of certain blood types, and this information is conveyed to the donor very clearly. If it is information about the scarcity, rather than information about one's motivation that is passed on between donors, then this effect should be stronger if the fellow tenants have the same blood type.

In order to test for this possibility, we augment the reduced form in the bivariate probit by interacting the phone call with the indicator $S_d = 1$ if both donors have the same blood type. We add the interaction with both, one's own phone call and the fellow tenant's phone call, since if $\delta > 0$ in the structural equation and both terms appear in the reduced form. Thus, we estimate

$$Y_{id}^* = \xi_0 + \xi_1 P_{id} + \xi_2 P_{-id} + \xi_3 P_{id} \times S_d + \xi_4 P_{-id} \times S_d + \xi_5 S_d + \xi_6' X_{id} + \xi_7' X_{-id} + u_{id} \,. \tag{4.1}$$

If information about the scarcity of the blood type is passed on fellow tenants, we'd expect ξ_2 to diminish relative to the baseline specification, and ξ_3 and ξ_4 to be significantly positive.

Table 5 displays the result. In the first two columns, it shows the reduced forms of the baseline specification with and without the indicator S_d. The third column, labeled "Validity Check 1", exhibits the the estimates of equation (4.1). As can be seen, the coefficients and standard errors on one's own phone call and the fellow tenant's phone call remain virtually unchanged. Furthermore, neither interaction with the same blood type within a dyad is statistically significant.

Thus, there is little evidence that information about the specific scarcity of the blood type is transmitted within dyads in a way that affects donations, while the two parameters identifying motivational spillovers are virtually unchanged.

A second, less specific way of checking for informational spillovers that would invalidate our identification strategy is based on the intuition that the phone calls may simply serve

Table 5: Bivariate probit model, reduced forms

Binary dependent variable: donation decision (0,1)				
Bivariate probit regression	Original Model	Augmented Original Model	Validity Check 1	Validity Check 2
	(Eq. 3.8)	(Eq. 3.8 aug.)	(Eq. 4.1)	(Eq. 4.2)
P_{1d}	0.274***	0.275***	0.257***	0.268***
	(0.049)	(0.049)	(0.050)	(0.052)
P_{2d}	0.106**	0.107**	0.090*	0.100*
	(0.051)	(0.051)	(0.053)	(0.053)
S_d		-0.046	-0.054*	
		(0.031)	(0.032)	
$S_d \times P_{1d}$			0.120	
			(0.132)	
$S_d \times P_{1d}$			0.041	
			(0.133)	
$P_{1d} \times P_{2d}$				0.036
				(0.109)
ρ	0.547***	0.547***	0.547***	0.547***
	(0.016)	(0.016)	(0.016)	(0.016)
Models additionally include reduced form parameters for X_{1d} and X_{2d} and a constant				
Location FEs?	yes	yes	yes	yes
Month FEs?	yes	yes	yes	yes
# of observations	10,120	10,120	10,120	10,120
# of dyads	3,723	3,723	3,723	3,723
Log likelihood	-10,883.35	-10,881.69	-10880.94	-10,883.3

Dyad cluster robust standard errors in parentheses.

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

Age normalized to sample average.

as a reminder of the blood drive. It is possible that that the phone call to one fellow tenant also reminds the other of the blood drive. In this case, a fellow tenant's phone call should have less of an effect on the other if the other received a phone call as well. This can be tested by augmenting the reduced form by an interaction between the two phone calls $P_{id} \times P_{-id}$. Under this sort of informational spillover, the coefficient of the interaction should be significantly negative. Thus, we estimate the equation

$$Y_{id}^{*} = \xi_0 + \xi_1 P_{id} + \xi_2 P_{-id} + \xi_3 P_{id} \times P_{-id} + \xi_4 S_d + \xi_5' X_{id} + \xi_6' X_{-id} + u_{id} \qquad (4.2)$$

The results of this validity check are displayed in the fourth column, labelled "Validity check 2" in Table 5. As can be seen, the point estimate of the interaction of the two phone calls is positive – the opposite of what one would expect if information about the drive was transmitted – and insignificant. Again, the two coefficients of the phone calls used to identify motivational spillovers are virtually unchanged and significant. Hence, there is no evidence against the validity of our instrument based on this more general sort of informational spillover about the blood.

4.3 Behavioral Heterogeneity

We next turn to examining heterogeneity with respect to the motivational spillovers. As discussed in section 2.2, our sample contains approximately 66 percent cohabiting couples and 34 percent neighbors at the same address. The motivational spillovers are possibly weaker among neighbors than among cohabiting couples. Furthermore, there is evidence of behavioral heterogeneity with respect to prosocial motivations, thus generating a further source of heterogeneity. We therefore estimate a finite mixture model that would pick up this sort of heterogeneity by identifying the different types of dyads.

However, the estimates of the finite mixture model provide no evidence for the existence of different types of dyads with distinct behavioral patterns. As shown in table 6, 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 dyads 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 dyads.

Table 6: *ICL-BIC* for determining the optimal number of types in a finite mixture model

	$K^* = 1$	$K = 2$	$K = 3$
ICL-BIC	23,731.05	26,448.43	28,132.61
BIC	23,731.05	23,369.67	23,332.60
Entropy	0	3,078.76	4,800.01

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

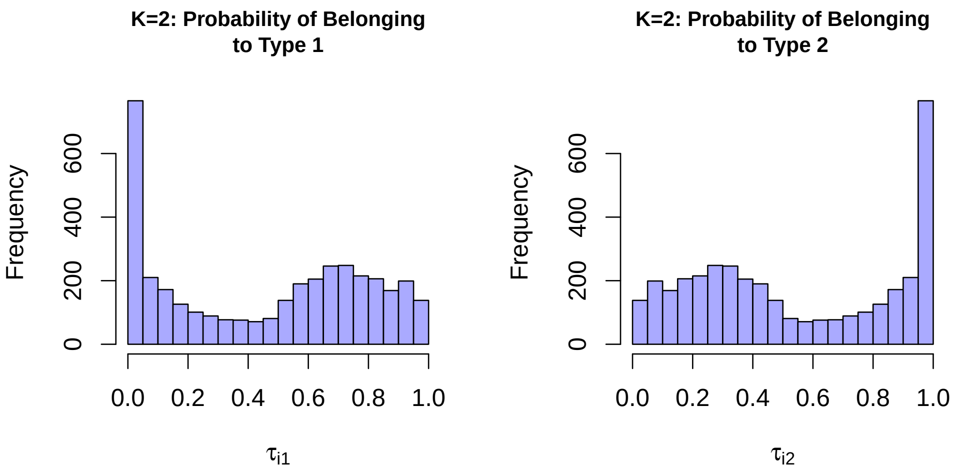

Figure 1: Ex-post probabilities of type-membership: model with $K = 2$ types

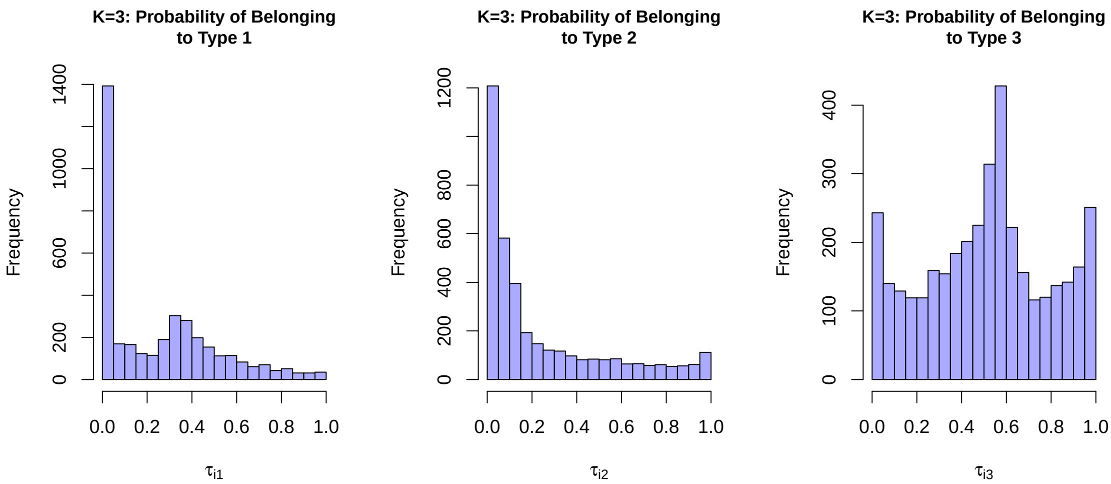

Figure 2: Ex-post probabilities of type-membership: model with $K = 3$ types

4.4 TSLS estimation of the "social multiplier"

In our baseline results, we use the bivariate probit model as our model of choice, as it follows directly from the random utility specification we adopt and allows us to model motivational spillovers explicitly. Furthermore, it also lends itself easily to be augmented for the finite mixture model in our search for behavioral heterogeneity. On the other hand, the model imposes more structure than is necessary to simply estimate the social multiplier in behavior. In this subsection, we reestimate our baseline model using a linear probability model and applying an instrumental variable (IV) strategy to estimate the effect of a fellow tenant's donation on the other's decision to give blood. As long as the conditional mean independence assumption and the exclusion restrictions are satisfied, this model provides a consistent estimate of the behavioral spillovers (Moffitt 1999). Estimating the linear probability model using an IV strategy allows us to see if the added "non-linearities" of the bivariate probit model bear any importance to our central conclusion of the paper, namely the quantitatively large social multiplier implied by our baseline results.

We apply the basic TSLS procedure to estimate the linear probability model. In the first stage, we predict the fellow tenant's donation, $\hat{Y}_{2dt}$, using the instrumental variable, P_{2dt}, and all exogenous variables by estimating the following linear model[8]:

$$Y_{2dt} = \eta_0 + \eta_1 P_{2dt} + \eta_2 P_{1dt} + \eta_3 X_{2dt} + \eta_4 X_{1dt} + \epsilon_{2dt}\,. \tag{4.3}$$

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

$$Y_{1dt} = \phi_0 + \phi_1 P_{1dt} + \phi_2 X_{1dt} + \phi_3 X_{2dt} + \phi_4 \hat{Y}_{2dt} + \epsilon_{1dt}\,. \tag{4.4}$$

Table 7 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, while (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 8 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 the standard tests for strong instruments (F-statics in the first stage: (1) 39.31, (2) 38.02, (3) 30.27, see Stock, Wright and Yogo (2002)). 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 endogenous social interaction which is robust to fixed effects. A donor's probability to give blood increases by about 40 percentage points if her fellow tenant donates. In this model, again, the social multiplier is given by $1/(1-\delta^2)$. With a value of about 1.25, it lies in the same range as in the bivariate probit model.

[8]Results of the first stage regression are reported in table 11 in the appendix.

Table 7: Linear probability model (second stage regressions)

Binary dependent variable: donation decision (0,1)			
OLS regression	(1)	(2)	(3)
Phone call (ϕ_1)	0.084***	0.083***	0.080***
	(0.023)	(0.022)	(0.021)
Endogenous Social Interaction (ϕ_4)	0.443***	0.435***	0.378**
	(0.161)	(0.165)	(0.179)
Constant (ϕ_0)	0.086***	0.065**	0.100*
	(0.026)	(0.032)	(0.053)
Donor's characteristics (ϕ_2)			
Male	0.034***	0.030***	0.031***
	(0.008)	(0.007)	(0.008)
Age	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)
# of donations in year before study (shares)			
1	0.163***	0.163***	0.166***
	(0.010)	(0.010)	(0.009)
2	0.296***	0.303***	0.305***
	(0.013)	(0.013)	(0.013)
3	0.366***	0.385***	0.389***
	(0.025)	(0.026)	(0.026)
4	0.347***	0.384***	0.374***
	(0.056)	(0.058)	(0.068)
Blood Types			
O-	0.011	0.010	0.013
	(0.021)	(0.021)	(0.020)
A+	-0.010	-0.009	-0.009
	(0.008)	(0.008)	(0.008)
A-	-0.006	-0.001	-0.001
	(0.016)	(0.015)	(0.015)
Fellow tenant's characteristics (ϕ_3)			
Male	-0.003	-0.007	-0.005
	(0.010)	(0.009)	(0.010)
Age	-0.002**	-0.002**	-0.002*
	(0.001)	(0.001)	(0.001)
# of donations in year before study (shares)			

1	-0.079***	-0.077***	-0.065**
	(0.028)	(0.028)	(0.031)
2	-0.132***	-0.122**	-0.103*
	(0.049)	(0.052)	(0.057)
3	-0.156**	-0.134*	-0.109
	(0.065)	(0.071)	(0.077)
4	-0.215***	-0.176*	-0.163
	(0.082)	(0.092)	(0.100)
Blood Types			
O-	-0.013	-0.015	-0.010
	(0.019)	(0.019)	(0.020)
A+	0.004	0.005	0.004
	(0.008)	(0.008)	(0.008)
A-	-0.028**	-0.022*	-0.021
	(0.013)	(0.013)	(0.013)
F-test of instrument (1. Stage)	39.31	38.02	30.27
F-tests for joint significance (p-value)			
Donor:			
all blood types	0.44	0.61	0.54
negative blood types	0.66	0.86	0.77
non O-negative blood types	0.40	0.49	0.48
Fellow tenant:			
all characteristics	0.01	0.09	0.22
previous donations	0.04	0.04	0.14
all blood types	0.12	0.25	0.32
negative blood types	0.10	0.23	0.27
Location FEs?	no	yes	yes
Month FEs?	no	no	yes
# of observations	20,240	20,240	20,240
# of dyads	3,723	3,723	3,723
R-squared	0.201	0.212	0.220

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 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 nearly 10 percent, male donors are about 3 percentage points more likely to donate blood than female donors. 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 8-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 donor's motivation (F-test for joint significance (1) p-value: 0.44, (2) p-value: 0.61, (3) p-value: 0.54). Donors with highly demanded, negative blood types do not exhibit higher donation rates (F-test for joint significance (1) p-value: 0.86, (2) p-value: 0.86, (3) p-value: 0.77). Similarly, the evidence of exogenous social interactions is weak in this specification as well.

4.5 The role of the age restriction

Perhaps the most arbitrary restriction in creating our sample is that we only consider dyads of fellow tenants with an age difference of less than 20 years. We motivated this restriction with previous evidence showing that individuals with strong social ties are most often close in age. However, it is nevertheless instructive to examine its role in our estimations. We reestimate the baseline specifications of the bivariate probit model in two alternative samples: one with an even stricter restriction on the intra-dyad age difference of less than 10 years, and one with no such age restriction at all.

Table 8 displays the results. We present the estimation results in a more compact form, focusing only on the estimates of the motivation spillovers δ, the impact of the phone call γ, and the estimate of the correlations in unobservables ρ to assess the sensitivity of our baseline estimates with regard to the different specifications of the age cutoff.

Panel A of table 8 shows the estimates for the first sample with the 10-year restriction on the intra-dyad age difference. This eliminates 509 dyads from our sample, shrinking the number of observations to $8,811$. The best available evidence (Kalmijn and Vermunt 2007) suggest that roughly 15 percent of one's close social ties have an age difference of more than 10 years. Since our restriction eliminates roughly the same number of dyads, this should not lead to a notable change in the likelihood of social ties within our sample. Consistent with this interpretation, the point estimates of δ are almost exactly the same as in our baseline specification, or perhaps slightly higher. This is also true for the other parameters of the model, as can be seen by the similarity of of the estimates for γ and ρ.

When we consider the second sample with no age restriction, the number of dyads increases from $3,723$ to $5,053$, a 35 percent increase. By contrast, evidence suggests that only roughly 10 percent of all social ties involve age differences of more than 20 years. Thus, relaxing the age restriction should add a disproportionate share of observations without social ties, which could decrease our estimates of δ. Panel B of table 8 displays the results. Indeed, there is somewhat of a decrease in the estimate of the spillover effects, though they remain within one standard error of our baseline estimates for each of the specifications, and are still significant for two of the three models. As before, there is virtually no change in the point estimate or precision of, i.e., the effectiveness of the phone call. Thus, there is no evidence that the additional observations generally are less predictable.

Overall, our conclusions are not sensitive to the age restriction. The point estimates do vary in the direction predicted by the evidence on social ties and age differences, with the point estimates being somewhat larger when the age restriction is tighter than when it is loosened; in particular when it adds a lot of observations known to be unlikely candidates for social ties.

Within our framework, we could also examine the sensitivity of our results by explicitly making ρ dependent on the age difference. Intuitively, this would add the interaction between the fellow tenant's phone call and the intra-dyad age difference as a restriction as an additional variable to the structural form equations 3.6 and 3.7. However, while our instrument is strong for the baseline specification, the instruments also using the interaction with the age difference fails the Kleinbergen-Paap criterion (Kleibergen and Paap 2006), possibly due to the collinearity between the two instruments. Due to this inherent source of ambiguity, we refrain from further exploring the issue.

Table 8: Bivariate probit model without age restriction

Panel A: Age difference restricted to less than 10 years			
Bivariate probit regression	(1)	(2)	(3)
Phone Reminder (γ)	0.216***	0.220***	0.214***
	(0.071)	(0.073)	(0.069)
Endogenous Social Interaction (δ)	0.475**	0.477**	0.419**
	(0.187)	(0.192)	(0.210)
ρ (correlation between residuals)	-0.303	-0.346	-0.219
	(0.440)	(0.438)	(0.485)
Location FEs?	no	yes	yes
Month FEs?	no	no	yes
# of dyads	3,214	3,214	3,214
# of observations	8,811	8,811	8,811
Log likelihood	-9,709.93	-9,461.13	-9,432.97

Panel B: No restriction on age difference			
Bivariate probit regression	(1)	(2)	(3)
Phone Reminder (γ)	0.254***	0.257***	0.243***
	(0.050)	(0.051)	(0.047)
Endogenous Social Interaction (δ)	0.325**	0.318**	0.243
	(0.150)	(0.156)	(0.172)
ρ (correlation between residuals)	-0.083	-0.107	0.050
	(0.333)	(0.343)	(0.364)
Location FEs?	no	yes	yes
Month FEs?	no	no	yes
# of dyads	5,053	5,053	5,053
# of observations	13,421	13,421	13,421
Log likelihood	-15,021.41	-14,667.31	-14,625.88

Household cluster robust standard errors in parentheses.

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

Age normalized to sample average.

5 Conclusion

In this paper we use a large panel data set with randomized phone calls to analyze the effects of social interaction on voluntary blood donations between fellow tenants. We find strong evidence for positive motivational spillovers, but no significant evidence for exogenous social interaction.

Overall, motivational spillovers have a forceful impact on donor motivation, as they generate a social multiplier that amplifies the direct impact of phone calls by 78 percent. It remains an open question as to what the precise psychological mechanism is behind the behavioral evidence of motivational spillovers. It may simply be more enjoyable to undertake an activity together, irrespective of whether it is a prosocial activity or not: going to an event in the company of a person with whom one has social ties may provide for better conservations on the way and while waiting. Alternatively, there may be image motivation involved specific to the prosocial activity, as one's fellow tenant witnesses one's prosocial act, in the spirit of Bénabou and Tirole (2006). It is also possible that our results pick up the interplay between pro-social individuals and conformists, who are more likely to donate if other do so as well, as suggested in Sliwka (2007). Surprisingly, there is no evidence for the existence different types of dyads that qualitatively differ in the extent or type of social interaction. Thus, explanations that rely on image motivation may be less intuitively appealing, as impressing one's spouse may not be quite so easy by simply donating blood. Ultimately, while our paper provides robust evidence for motivational spillovers, it is unable to pin down the precise psychological mechanism behind it. This does not, however, affect their policy relevance for the application at hand.

The main finding of motivational spillovers has several policy implications. First, these motivational spillovers among donors are strong, and could therefore offset diminishing returns of policy interventions via social multipliers. Thus, applying policy interventions to groups of donors in which motivational spillovers are likely present and strong – such as couples, flat mates, families, sports clubs, or churches, for example – is more cost-effective than targeting independent individuals. Second, facilitating motivational spillovers and especially encouraging donors to announce their support of blood donation within their social network could increase donation rates significantly. For example, blood donation services could use virtual social networks that allow blood donors to communicate their donations to individuals with whom they have social ties, without the need of physical proximity. All these conjectures lend themselves to empirical tests for future research.

The policy implications of motivational spillovers are not confined to voluntary blood donations but also apply to other fields in which endogenous social interaction plays an important role. There are many other potential settings in which similar mechanisms may be operating, such as volunteering, or other civic engagements like turning out to vote or attending town hall meetings. Future research should address these questions.

A Appendix

A.1 Recovering parameters from reduced form

Express equation 3.8 as

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

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

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

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

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 can be computed by 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.2 Marginal effects in the bivariate probit model

Define $Z_d = (P_d, Y_d^*, X_d)$, $\zeta = (\gamma, \delta, \beta')'$. The discrete probability effect of the phone reminder holding the social interaction effects constant is given by

$$\Delta P_{call} \equiv \Phi\left(\gamma_1 + \zeta'\overline{Z_d}\right) - \Phi\left(\zeta'\overline{Z_d}\right). \tag{A.2}$$

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

$$\Delta P_1 \equiv \Phi\left(\frac{\gamma_1}{1-\delta^2} + \zeta'\overline{Z_d}\right) - \Phi(\zeta'\overline{Z_d}), \tag{A.3}$$

where $1/(1-\delta^2)$ is the social multiplier discussed in section 4. Similarly, the effect on the fellow tenant not receiving a phone call is given by

$$\Delta P_2 \equiv \Phi\left(\frac{\gamma_1\delta}{1-\delta^2} + \zeta'\overline{Z_d}\right) - \Phi(\zeta'\overline{Z_d}), \tag{A.4}$$

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

A.3 Pooled bivariate probit model without age restriction

Table 9: Bivariate probit model without age restriction

Binary dependent variable: donation decision (0,1)			
Bivariate probit regression	(1)	(2)	(3)
Phone Reminder (γ)	0.254***	0.257***	0.243***
	(0.050)	(0.051)	(0.047)
Endogenous Social Interaction (δ)	0.325**	0.318**	0.243
	(0.150)	(0.156)	(0.172)
Constant (β_0)	-0.677***	-0.867***	-0.884***
	(0.153)	(0.229)	(0.258)
Donor's characteristics (β_1)			
Male	0.122***	0.117***	0.119***
	(0.020)	(0.020)	(0.021)
Age	0.011***	0.012***	0.011***
	(0.001)	(0.001)	(0.001)
# of donations in year before study			
1	0.527***	0.550***	0.561***
	(0.026)	(0.026)	(0.026)
2	0.888***	0.949***	0.961***
	(0.031)	(0.033)	(0.033)
3	1.094***	1.207***	1.224***
	(0.056)	(0.061)	(0.062)
4	0.906***	1.021***	1.012***
	(0.119)	(0.130)	(0.141)
Blood Types			
O-	0.014	0.015	0.028
	(0.051)	(0.052)	(0.051)
A+	-0.022	-0.020	-0.020
	(0.021)	(0.021)	(0.021)
A-	0.009	0.022	0.023
	(0.040)	(0.041)	(0.040)
Fellow tenant's characteristics (β_2)			
Male	-0.018	-0.025	-0.016
	(0.027)	(0.027)	(0.029)
Age	-0.005**	-0.004**	-0.004*

	(0.002)	(0.002)	(0.002)
# of donations in year before study			
1	-0.188**	-0.181**	-0.131
	(0.082)	(0.089)	(0.100)
2	-0.293**	-0.262*	-0.183
	(0.136)	(0.153)	(0.170)
3	-0.368**	-0.283	-0.185
	(0.173)	(0.203)	(0.224)
4	-0.273	-0.172	-0.112
	(0.325)	(0.329)	(0.346)
Blood Types			
O-	-0.028	-0.027	-0.012
	(0.049)	(0.051)	(0.053)
A+	0.005	0.007	0.006
	(0.021)	(0.022)	(0.022)
A-	-0.074**	-0.070*	-0.064
	(0.037)	(0.039)	(0.040)
ρ (correlation between residuals)	-0.083	-0.107	0.050
	(0.333)	(0.343)	(0.364)
Wald-tests for joint significance (p-value)			
Fellow tenant:			
All characteristics	0.14	0.28	0.29
Location FEs?	no	yes	yes
Month FEs?	no	no	yes
# of observations	13,421	13,421	13,421
# of dyads	5,053	5,053	5,053
Log likelihood	-15,021.41	-14,667.31	-14,625.88

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 Finite mixture regression results

Table 10: Finite mixture model with $K = 2$ types

Binary dependent variable: donation decision (0,1)		
Bivariate probit regression	Type 1 Donors	Type 2 Donors
Phone Reminder (γ_k)	0.052	0.209**
	(0.336)	(0.100)
Endogenous Social Interaction (δ_k)	0.937**	-0.181
	(0.412)	(0.446)
Constant (β_{0k})	-0.147	-0.808*
	(0.957)	(0.446)
Donor's characteristics (β_{1k})		
Male	0.022	0.082
	(0.164)	(0.068)
Age	0.058***	0.005
	(0.021)	(0.008)
# of donations in year before study		
1	1.829***	0.478***
	(0.414)	(0.091)
2	2.610***	0.738***
	(0.432)	(0.149)
3	3.429***	0.888***
	(0.788)	(0.196)
4	3.041***	0.435
	(0.574)	(0.426)
Blood Types		
O-	-0.110	0.096
	(0.239)	(0.099)
A+	-0.021	0.009
	(0.124)	(0.090)
A-	0.052	0.048
	(0.221)	(0.077)
Fellow tenant's characteristics (β_{2k})		
Male	0.013	-0.016
	(0.230)	(0.044)

Age	-0.057**	0.007***
	(0.028)	(0.002)
# of donations in year before study		
1	-1.769*	0.274**
	(1.035)	(0.126)
2	-2.507***	0.436
	(0.941)	(0.304)
3	-3.322*	0.645**
	(1.893)	(0.268)
4	-2.868**	-0.113
	(1.357)	(0.238)
Blood Types		
O-	0.100	-0.003
	(0.217)	(0.061)
A+	0.011	0.043
	(0.064)	(0.064)
A-	-0.077	-0.019
	(0.228)	(0.037)
ρ_k (correlation between residuals)	-0.988***	0.670
	(0.170)	(0.509)
π_k (share among the population)	0.456	0.544
	(0.060)	(0.060)
Location FEs?	yes	
Month FEs?	yes	
# of observations	10,120	
# of dyads	3,723	
Log likelihood	-10,596.61	

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.5 First stages of 2SLS

Table 11: Linear probability model (first stage regressions)

Binary dependent variable: fellow tenant's donation decision (0,1)			
OLS regression	(1)	(2)	(3)
Constant (η_0)	0.154***	0.114**	0.161**
	(0.015)	(0.047)	(0.073)
Fellow tenant's Phone	0.104***	0.102***	0.093***
Reminder (η_1)	(0.017)	(0.017)	(0.017)
Donor's Phone	0.046***	0.045***	0.035**
Reminder (η_2)	(0.016)	(0.017)	(0.017)
Fellow tenant's characteristics (η_3)			
Male	0.041***	0.033***	0.034***
	(0.010)	(0.010)	(0.010)
Age	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)
# of donations in year before study			
1	0.159***	0.160***	0.165***
	(0.009)	(0.009)	(0.009)
2	0.295***	0.308***	0.311***
	(0.012)	(0.012)	(0.012)
3	0.370***	0.403***	0.406***
	(0.024)	(0.025)	(0.025)
4	0.313***	0.379***	0.365***
	(0.099)	(0.105)	(0.110)
Blood Types			
O-	0.007	0.004	0.010
	(0.020)	(0.020)	(0.020)
A+	-0.011	-0.008	-0.009
	(0.009)	(0.008)	(0.008)
A-	-0.023	-0.013	-0.010
	(0.015)	(0.015)	(0.015)
Donor's characteristics (η_4)			
Male	0.015	0.007	0.008
	(0.010)	(0.010)	(0.010)
Age	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)

# of donations in year before study			
1	-0.009	-0.008	-0.003
	(0.009)	(0.009)	(0.009)
2	-0.001	0.012	0.015
	(0.012)	(0.012)	(0.012)
3	0.008	0.041*	0.044*
	(0.024)	(0.024)	(0.024)
4	-0.077	-0.011	-0.025
	(0.105)	(0.110)	(0.114)
Blood Types			
O-	-0.010	-0.013	-0.006
	(0.018)	(0.019)	(0.019)
A+	-0.001	0.002	0.001
	(0.009)	(0.008)	(0.008)
A-	-0.038**	-0.028*	-0.025*
	(0.015)	(0.015)	(0.015)
F-tests of instrument	39.31	38.02	30.27
Location FEs?	no	yes	yes
Month FEs?	no	no	yes
# of observations	20,240	20,240	20,240
# of dyads	3,723	3,723	3,723
R-squared	0.084	0.118	0.122

Household cluster robust standard errors in parentheses.

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

Age normalized to sample average.

References

Abadie, Alberto. 2000. "Semiparametric Estimation of Instrumental Variable Models for Causal Effects.". Technical Working Paper 260.

Angrist, Joshua D. 2001. "Estimation of Limited Dependent Variable Models With Dummy Endogenous Regressors." *Journal of Business and Economic Statistics* 19(1).

Atkinson, Anthony C. 1981. "Likelihood Ratios, Posterior Odds and Information Criteria." *Journal of Econometrics* 16(1):15–20.

Bénabou, Roland and Jean Tirole. 2003. "Intrinsic and Extrinsic Motivation." *Review of Economic Studies* 70:489–520.

Bénabou, Roland and Jean Tirole. 2006. "Incentives and Prosocial Behavior." *The American Economic Review* 96:1652–1678.

Bénabou, Roland and Jean Tirole. 2011. "Identity, morals, and taboos: Beliefs as assets." *The Quarterly Journal of Economics* 126(2):805–855.

Biernacki, Christophe, Gilles Celeux and Gérard Govaert. 2000*a*. "Assessing a Mixture Model for Clustering with the Integrated Completed Likelihood." *IEEE Trans. Pattern Anal. Mach. Intell.* 22(7):719–725.

Biernacki, Christophe, Gilles Celeux and Gérard Govaert. 2000*b*. "An Improvement of the NEC Criterion for Assessing the Number of Clusters in a Mixture Model." *Pattern Recognition Letters* 20(3):267–272.

Borjas, George J. and Kirk B. Dorani. 2014. "Which Peers Matter? The Relative Impacts of Collaborators, Colleagues, And Competitors.". Working Paper 20026, National Bureau of Economic Research.

Bowles, Samuel and Herbert Gintis. 2002. "Social capital and community governance*." *The Economic Journal* 112(483):F419–F436.

Breitmoser, Yves. 2013. "Estimation of Social Preferences in Generalized Dictator Games." *Economics Letters* 121(2):192–197.

Bruhin, Adrian, Ernst Fehr and Daniel Schunk. 2014. "The Many Faces of Human Sociality - Uncovering the Distribution and Stability of Social Preferences.". Working Paper.

Bruhin, Adrian, Helga. Fehr-Duda and Thomas Epper. 2010. "Risk and Rationality: Uncovering Heterogeneity in Probability Distortion." *Econometrica* 78(4):1375–1412.

Bruhin, Adrian and Lorenz Goette. 2014. "Call of Duty: The Impact of Behavioral Interventions on Blood Donations.". Working Paper.

Celeux, Gilles and Gilda Soromenho. 1996. “An Entropy Criterion for Assessing the Number of Clusters in a Mixture Model.” *Journal of Classification* 13(2):195–212.

Cipollone, Piero and Alfonso Rosolia. 2007. “Social Interactions in High School: Lessons from an Earthquake.” *The American Economic Review* 97(3).

Conte, Anna, John D. Hey and Peter. G. Moffat. 2011. “Mixture Models of Choice Under Risk.” *Journal of Econometrics* 162(1):79–88.

Durlauf, Steven. 2002. “On The Empirics Of Social Capital*.” *The Economic Journal* 112(483):F459–F479.

Falk, Armin and Urs Fischbacher. 2002. “Crime in the lab-detecting social interaction.” *European Economic Review* 46(4):859–869.

Fehr, Ernst and Urs Fischbacher. 2004. “Social norms and human cooperation.” *Trends in cognitive sciences* 8(4):185–190.

Fischbacher, Urs, Simon Gächter and Ernst Fehr. 2001. “Are people conditionally cooperative? Evidence from a public goods experiment.” *Economics Letters* 71(3):397–404.

Frey, Bruno S. and Stephan Meier. 2004. “Social comparisons and pro-social behavior: Testing” conditional cooperation” in a field experiment.” *American Economic Review* 95(5):1717–1722.

Geweke, John and Richard Meese. 1981. “Estimating Regression Models of Finite but Unknown Order.” *Journal of Econometrics* 16(1):162–162.

Goette, Lorenz and Alois Stutzer. 2008. “Blood Donations and Incentives: Evidence from a Field Experiment.”. Discussion Paper No. 3580.

Goette, Lorenz, Alois Stutzer, Gürcan Yavuzcan and Beat M. Freydur. 2009. “Free Cholesterol Testing as A Motivation Device in Blood Donations: Evidence from Field Experiments.” *Transfusion* 49(March):524–531.

Goette, Lorenz, David Huffman and Stephan Meier. 2006. “The Impact of Group Membership on Cooperation and Norm Enforcement: Evidence Using Random Assignment to Real Social Groups.” *American Economic Review* 96(2):212–216.

Greene, William H. 2003. *Econometric analysis*. Pearson Education India.

Harrison, Glenn W. and Elisabet E. Rutström. 2009. “Representative Agents in Lottery Choice Experiments: One Wedding and A Decent Funeral.” *Experimental Economics* 12(2):133–158.

Houser, Daniel, Michael Keane and Kevin McCabe. 2004. “Behavior in a Dynamic Decision

Problem: An Analysis of Experimental Evidence using a Bayesian Type Classification Algorithm." *Econometrica* 72(3):781–822.

Huber, Peter J. 1967. The Behavior of Maximum Likelihood Estimates under Nonstandard Conditions. In *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability.* University of California Press.

Iriberri, Nagore and Pedro Rey-Biel. 2013. "Elicited Beliefs and Social Information in Modified Dictator Games: What Do Dictators Believe Other Dictators Do." *Quantitative Economics* 4(3):515–547.

Kalmijn, Matthijs and Jeroen K. Vermunt. 2007. "Homogeneity of social networks by age and marital status: A multilevel analysis of ego-centered networks." *Social Networks* 29(1):25 – 43.

Kessler, Judd B. 2013. "Announcements of Support and Public Good Provision.".

Kleibergen, Frank and Richard Paap. 2006. "Generalized reduced rank tests using the singular value decomposition." *Journal of Econometrics* 133(1):97–126.

Knack, Stephen and Philip Keefer. 1997. "Does social capital have an economic payoff? A cross-country investigation." *The Quarterly journal of economics* 112(4):1251–1288.

Lacetera, Nicola and Mario Macis. 2012b. "Time for Blood: The Effect of Paid Leave Legislation on Altruistic Behavior." *Journal of Law, Economic, and Organization* 29(6):1384–1420.

Lacetera, Nicola, Mario Macis and Robert Slonim. 2012a. "Will There Be Blood? Incentives and Displacement Effects in Pro-Social Behabior." *American Economic Journal* 4(1):186–223.

Lacetera, Nicola, Mario Macis and Robert Slonim. 2014. "Rewarding Volunteers: A Field Experiment." *Management Science* 60(5):1107–1129.

Lalive, Rafael and M. Alejandra Cattaneo. 2009. "Social Interactions and Schooling Decisions." *The Review of Economics and Statistics* 91(3):457–477.

Leider, Stephen, Markus M. Möbius, Tanya Rosenblat and Quoc-Anh Do. 2009. "Directed Altruism and Enforced Reciprocity in Social Networks." *The Quarterly Journal of Economics* 124(4):1815–1851.

Leider, Stephen, Tanya Rosenblat, Markus M. Möbius and Quoc-Anh Do. 2010. "What do we Expect from our Friends?" *Journal of the European Economic Association* 8(1):120–138.

Lo, Yungtai, Nancy R. Mendell and Donald B. Rubin. 2001. "Testing the number of components in a normal mixture." *Biometrika* 88(3):767–778.

Manski, Charles F. 1993. "Identification of Endogenous Social Effects: The Reflection Problem." *The Review of Economics Studies* 60(3):531–542.

Manski, Charles F. 2000. "Economic Analysis of Social Interactions.". Working Paper 7580.

Marmaros, David and Bruce Sacerdote. 2006. "How Do Friendships Form?" *The Quarterly Journal of Economics* 121(1):79–119.

Marsden, Peter V. 1988. "Homogeneity in confiding relations." *Social Networks* 10(1):57 – 76.

McLachlan, Geoffrey and David Peel. 2000. *Finite mixture models*. John Wiley & Sons.

McPherson, Miller, Lynn Smith-Lovin and James M. Cook. 2001. "Birds of a Feather: Homophily in Social Networks." *Annual Review of Sociology* 27(1):415–444.

Moffitt, Robert A. 1999. "New developments in econometric methods for labor market analysis." *Handbook of Labor Economics* 3:1367–1397.

Muthén, Bengt. 2003. "Statistical and Substantive Checking in Growth Mixture Modeling: Comment on Bauer and Curran (2003).".

Niessen-Ruenzi, Alexandra, Martin Weber and David M. Becker. 2014. "To Pay or Not to Pay-Evidence from Whole Blood Donations in Germany.".

Olken, Benjamin A. 2009. "Do television and radio destroy social capital? Evidence from Indonesian villages." *American Economic Journal: Applied Economics* 1(4):1–33.

Putnam, Robert D. 2000. *Bowling alone: The collapse and revival of American community*. Simon and Schuster.

Shang, Jen and Rachel Croson. 2009. "A field experiment in charitable contribution: The impact of social information on the voluntary provision of public goods." *The Economic Journal* 119(540):1422–1439.

Sliwka, Dirk. 2007. "Trust as a Signal of a Social Norm and the Hidden Costs of Incentive Schemes." *The American Economic Review* 97(3):999–1012.

Stock, James H., Jonathan H. Wright and Motohiro Yogo. 2002. "A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments." *Journal of Business & Economic Statistics* 20(4):518–29.

Twenge, Jean M., Roy F. Baumeister, C. Nathan DeWall, Natalie J. Ciarocco and J. Michael

Bartels. 2007. "Social exclusion decreases prosocial behavior." *Journal of personality and social psychology* 92(1):56.

Vuong, Quang H. 1989. "Likelihood Ratio Tests for Model Selection and Non-Nested Hypotheses." *Econometrica* 57(2):307–333.

Wildman, John and Bruce Hollingsworth. 2009. "Blood Donation and The Nature of Altruism." *Journal of Health Economics* 28(2):492–503.

Winkelmann, Rainer. 2012. "Copula Bivariate Probit Models: With an Application to Medical Expenditures." *Health Economics* 21(12):1444–1455.

Wooldridge, Jeffrey. M. 2002. *Econometric Analysis of Cross Section and Panel Data*. MIT Press.

World Health Organization. 2011. "Global Database on Blood Safety." *Summary Report* .