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

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Abstract

Spillovers of prosocial motivation can enhance the provision of public goods, and have implications for the cost-benefit analysis of policy interventions. We analyze a large-scale intervention among dyads of pre-registered blood donors. A quasi-random phone call provides the instrument for identifying endogenous and exogenous social interaction. The phone call has a strong effect on the recipient's propensity to donate. Between 40% and 44% of that behavioral impulse is transmitted within dyads due to motivational spillovers. This creates a significant social multiplier to policy interventions, with estimates ranging between 1.6 and 1.8. There is no evidence for exogenous social interaction.

Keywords: Social Interaction, Social Ties, Prosocial Motivation, Blood Donation, Bivariate Probit

JEL Classificattion: D03, C31, C36, C93

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1 Introduction

Many public goods benefit a diffuse and large number of individuals, yet they require the individual contributions of many. Examples include donating money and time to help sustain charities, participating in civic duties such as schoolboard meetings and neighborhood associations, or being an informed citizen and participating in elections and referenda. In this context, it has often been argued that the effective provision of public goods requires a social fabric underlying it (Putnam 2000; Durlauf 2002). For example, Putnam (2000) famously argued that the decline in civic activities in the US, that severed social ties between individuals in communities, caused a sharp reduction in prosocial behavior.[1]

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 contribute (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. Another plausible mechanism is joint consumption. Engaging in a prosocial activity such as attending a school meeting, blood drive, or turning out to vote may be more enjoyable – or less costly – in the company of others. This, again, creates a motivational spillover: if it is more likely that others engage in a prosocial activity, an individual's utility from engaging in the activity as well increases. The latter two mechanisms stand out since they generate a "social multiplier" that lies at the heart of social capital. If 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.

Previous research also suggests that motivational spillovers are particularly strong between individuals connected with strong social ties (McAdam 1986). Several studies show that altruism is stronger between individuals who are socially connected, even under laboratory anonymity (Twenge et al. 2007; Goette, Huffman and Meier 2006; Leider et al. 2010). Social ties may also be particularly important in field settings. Indeed correlational evidence on social networks suggests that motivation spillovers may occur along strong social ties (O'Malley et al. 2012).

In this paper, we investigate whether social ties lead to motivational spillovers in the context of voluntary blood donations. Voluntary blood donations are a textbook example of prosocial behavior that benefits a large number of individuals. 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; Slonim, Wang and Garbarino 2014). Studying motivations to donate blood is instructive to understand a wide class of prosocial behaviors, such as volunteering, voting or other civic activities, in which spillovers of motivation may occur.

[1]See Olken (2009) for an empirical test of this mechanism.

We use data from individuals that are pre-registered for blood drives at 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 pre-registered individuals in our sample who live at a street address with exactly one fellow tenant who is also pre-registered 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 individuals are invited repeatedly to blood drives, creating 10,120 observations of dyads, with each individual deciding whether or not to donate.[2] In every dyad, each of the two individuals received a personalized invitation letter for the upcoming blood drive and a text message on her mobile phone reminding her of the event. In the context of Switzerland (and much of Europe), most people live in apartment buildings, with only 15% living in single-family homes (Bundesamt für Statistik 2014). Thus, focusing on individuals with the same street address is a natural starting point.

Identifying social interaction is difficult (Manski 2000; Durlauf 2002): simply observing a correlation in behavior within dyads is not necessarily evidence of social interaction. Both individuals may be exposed to a similar environment, thus experiencing correlated shocks to their propensity to donate that generate an omitted-variable bias which exaggerates the causal effect of social interaction. Furthermore, it is hard to distinguish endogenous from exogenous social interaction. With endogenous social interaction, the fellow tenant's propensity to donate is directly affected by the other individual's propensity to donate, whereas under exogenous social interaction, it is influenced by the other individual's characteristics. The distinction between these two types of social interaction is policy relevant. As endogenous social interaction effects go in both directions and result in a feedback loop between the two individuals within a dyad, they create a social multiplier that could greatly amplify the effectiveness of policy interventions. Exogenous social interaction effects, on the other hand, go just in one direction and do not create any social multipliers. Finally, the presence of endogenous social interaction itself creates an endogeneity problem between the two individuals within a dyad. If the propensity to donate spills from one individual to her fellow tenant, that propensity (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 an individual's propensity to donate but leaves her other characteristics as well as her fellow tenant's propensity to donate unaffected. We use a phone call to a subset of the invited individuals two days before the blood drive, asking them to donate because their blood types are in short supply at the moment. It satisfies the previous two requirements for an instrument. First, because the phone call is randomized conditional on blood type, it is exogenous to the recipient's other characteristics and her propensity to donate. Second, the phone call directly increases the recipient's propensity to donate (Bruhin et al. 2015), but leaves the fellow tenant's propensity to donate unaffected, unless the individuals within the dyad interact. Note also, that since all individuals already received a personalized invitation for the upcoming blood drive and a text message

[2]Blood drives are special events where individuals come and donate 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.

reminding them of the event, the only additional information conveyed by the phone call is the scarcity of its recipient's specific blood type.[3]

We apply a linear-in-motivation model adapted from Manski (1993) in a bivariate probit specification. This allows us to distinguish endogenous from exogenous social interaction effects, without imposing restrictive assumptions on how contextual effects affect donations.

Overall, we find strong evidence for endogenous social interaction effects. The estimates of our baseline specification imply that 44 percent of the change in an individual's propensity to donate directly spills over to her fellow tenant's propensity to donate. Calling up the individual raises her propensity to donate by roughly 12 percentage points (over a baseline of roughly 30 percentage points). The phone call also raises her fellow tenant's propensity to donate by 5 percentage points. The finding is robust, as depending on the specification, 40 to 44 percent of the change in the individual's propensity to donate is transmitted to her fellow tenant.

An important question is whether there are also exogenous social interaction effects arising due to attributes to which the fellow tenant reacts. Our setup and the bivariate probit model allow us to identify such exogenous social interaction effects: our dataset contains various characteristics of the individuals that strongly predict blood donations, such as age and the number of donations in the year prior to the beginning of the intervention study. These characteristics, in combination with the time-varying instrument, allow us to disentangle endogenous from exogenous social interaction effects. We find no evidence that individuals respond to some exogenous characteristics of the fellow tenant that generally predict donations.

Having established strong endogenous social interaction effects, we are also able to better understand the mechanisms driving them. In particular, is it motivation that is transmitted between fellow tenants or perhaps information (about the current scarcity of a specific blood type in our case)? Previous studies that found evidence of peer effects point to information rather than motivation transmission: Drago, Mengel and Traxler (2013) show that reminders about one's obligation to pay TV dues spread to neighbors who were not targeted by the mailing, even when the recipient of the reminder was already previously complying. Duflo and Saez (2003) show that information about pension plans spreads similarly among work colleagues. In the context of blood donations, Lacetera, Macis and Slonim (2014) announce to a subset of blood donors that they will be given a stored-value card if they donate blood. Interestingly, they find that the incentive effects also percolate to other donors who were not made aware of the incentives, again pointing to information as the driver of the peer effect. On the other hand, studies that examine the role of peer effects in work effort find that it is the behavior, rather than information, that is transmitted. For instance, Mas and Moretti (2009) exploit random assignment of clerks to check stands. They find strong spillovers of productivity. They argue that the most likely explanation of their finding is peer pressure, since their results indicate that only workers in sight of a coworker are affected by her productivity (see also Herbst and Mas 2015).

[3]We apply a strict intention-to-treat (ITT) methodology regarding the phone call: we only consider whether an individual was on a call list, not whether the call was answered in person, whether a message was left on the answering machine, or whether the call was even made. This ITT approach only affects the interpretation of the direct effect of the phone call, not the identification of the endogenous social interaction.

We are able to test whether information is transmitted in our setting in two ways. First, we examine whether a phone call to an individual with a blood type that is incompatible with the fellow tenant's blood type also affects the fellow tenant's propensity 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 individuals with incompatible blood types, or at least significantly weaker.[4] However, we find the same effect as for individuals with compatible blood types. Second, we check whether a phone call to an individual is ineffective if the fellow tenant also was called by the BTSRC. Again, in case the information mattered, we would expect the effect to be weaker if both individuals of a dyad received a phone call, but we find no evidence thereof. Thus, our evidence suggests that it is motivation, not information, that is transmitted between the individuals in a dyad. It is, to our knowledge, the first study to document spillovers of prosocial motivation in the field.

With an estimated two thirds of our sample being cohabiting couples, it is also interesting to ask whether spillovers are confined to them or whether they are present among all dyads in our sample.[5] Because cohabitation is not directly observable, we apply a finite mixture model to detect heterogeneity in motivational spillovers. The panel structure of our data and the modeling of the individuals' donation decisions within a bivariate probit model lends itself to an analysis with a finite mixture model. However, when we search in the data for latent 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.

In sum, our study provides strong support for the notion that prosocial motivation can spill over between individuals with social ties. These motivational spillovers alter the cost-benefit calculations of policy interventions in important ways: the estimates of our baseline specification indicate that 44 percent of the initial impulse on motivation from the phone call spills over to the fellow tenant. In turn, 44 percent of that increase in the fellow tenant's motivation spills back to the individual being called, and so on. The resulting feedback loop creates a social amplification effect of $1/(1-0.44^2)$ for the individual being called, and raises the fellow tenant's motivation by a fraction $0.44/(1-0.44^2)$. Overall, the resulting social multiplier is the sum of the two, and in our case, equals to $1/(1-0.44) = 1.79$. Even in our strictest specification, we find that 37 percent of the motivation spills over to the fellow tenant, yielding a lower-bound multiplier of $1/(1-0.37) = 1.63$. Thus, motivational spillovers raise the effectiveness of policy interventions by 60 to 80 percent. This social multiplier affects optimal policy, as a behavioral intervention has substantially higher benefits when targeted towards dyads instead of isolated individuals.

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 interpretation, we also find significant spillover effects in the TSLS specification, and virtually the same implied social multiplier.

[4] If an individual has a blood type that is incompatible with the one in shortage, then donating her blood does not help to reduce the shortage (for instance, someone with blood type B+ donating her blood when blood type A- is in shortage.). Therefore, she should not react to the information of the phone call as strong as if she would have a compatible blood type.

[5] We do not observe cohabitation directly. However, our data indicate that 83% of the dyads are opposite-sex dyads. Denote by x the fraction of cohabiting couples. Under random matching for non-cohabiting tenants, x is given by $x + (1-x) \cdot 0.5 = 0.83$, which yields $x = 0.66$.

This study directly contributes to the existing empirical literature on voluntary blood donation. Previous studies have mainly focused on finding behavioral interventions that increase individual motivations and are relatively cost effective. Several studies examine the impact of offering cash-like incentives such as gift cards (Lacetera, Macis and Slonim 2012a; Ferrari et al. 1985; 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 a phone call pointing out the scarcity of their blood type (Bruhin et al. 2015) or highlighting the emphatic motive in a personal phone call to donors (Reich et al. 2006) are also highly effective.[6]

As mentioned previously, Lacetera, Macis and Slonim (2014) implemented randomized interventions, informing half of the donors in an intervention blood drive that they would receive a cash-like reward if they donated blood, while leaving the other half uninformed about this reward. At control drives, no one was informed that they would receive a reward, even though they did. They find that donors who were directly informed of the reward have a significantly higher propensity to donate blood than donors at control drives. Interestingly, also the uninformed donors at intervention drives had a higher probability to donate blood of roughly half the size of the informed donors' treatment effect. Lacetera, Macis and Slonim (2014) provide clear evidence of social influence among donors. Their results are consistent with the interpretation that donors spread the information about the incentives to other potential donors they know, thus creating an indirect treatment effect on the uninformed donors. By contrast, our setting focuses on the transmission of donor motivation, independently of the social transmission of information about incentives. These results, taken together, suggest a pervasive impact of social ties on blood donations, and raise the prospect that informational and motivational spillovers are pervasive in other forms of prosocial behavior as well.

The present study also adds to the broader literature that distinguishes between endogenous and exogenous social interaction and 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 empirical set up. Section 3 presents the econometric analysis. Section 4 discusses the results and some robustness checks. Finally, section 5 concludes.

[6] See Goette, Stutzer and Frey (2010) or Lacetera, Macis and Slonim (2013) for a more extensive review.

2 The Empirical Setup

This section discusses the origin and structure of the panel data set, how we isolate dyads of fellow tenants with potential social ties, and the phone call we use as instrument for identifying social interaction effects.

2.1 Origin and Structure of the Data

The panel data set contains information about all 40,617 individuals who are pre-registered in the BTSRC's data base as they made at least one donation prior to the onset of the study. During the study period from April 2011 to January 2013, the BTSRC repeatedly invited these individuals to upcoming blood drives. These are regular events, typically taking place twice a year, at which donations can be made.[7] The blood drives are coordinated by local organizations, such as church chapters or sports clubs, but organized centrally by the BTSRC which administers the invitation of individuals and provides the equipment and personnel to take blood. The invitation procedure works as follows: For each upcoming blood drive, the BTSRC sends a personalized invitation letter to all eligible individuals pre-registered in its data base, i.e. individuals who did not donate within the past three months and meet all donation criteria. All invited individuals additionally receive a text message on their mobile phones 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. On average, each of the 40,617 pre-registered individuals received 3.09 invitations, resulting in 125,692 observations.

For each observation, the data set contains the following information: a binary indicator whether the individual donated at the blood drive she was invited to, her street (in a codified 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 beginning of the study. Moreover, we also observe whether the individual additionally received a phone call, informing her that her blood type is currently in short supply.

2.2 Dyads of Fellow Tenants

To test for social interaction effects, we aim to focus on individuals with strong social ties. However, in our data set, we only observe a limited set of individual characteristics due to the physician patient privilege. Thus, we first draw on earlier evidence that shows that proximity is an important predictor of social ties. Marmaros and Sacerdote (2006) report that random allocations to university dorms strongly predict 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. Second, we use evidence that friends are often very close in age: several studies document that friendship pairs typically 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).

[7]The BTSRC also operates fixed donation centers which we do not consider as the invitations procedure is different.

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
Age	43.186	11.850	0.859
Male	0.511	0.500	mixed-gender dyads: 83%
# of observations	$10,120$		
# of dyads	$3,723$		

In this spirit, we first define groups of fellow tenants, invited to the same blood drive, by exploiting the available information on the individuals' place of residence. Note, however, the codified address only allows us to determine whether the individuals live in the same building with a given house number, but not whether they are actually friends or partners living in the same household or just neighbors living in the same apartment building.

We restrict our attention to dyads of fellow tenants, i.e. pairs, for the following two reasons. First, eliminating large groups of fellow tenants, increases the probability that two individuals interact with each other. With a third individual present, it is more likely that the individuals are neither friends with each other nor partners. Second, by focussing on dyads, we can apply 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 individual-level.

Subsequently, as motivated by the studies cited above, we limit the age difference between the two fellow tenants within each dyad to less than 20 years. 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 of dyads we use for the estimation. The average age of our individuals is 43 years, and 51 percent of them 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 fellow tenants are cohabiting (heterosexual[8]) couples, assuming that for non-cohabiting tenants, the gender composition is random. Simple calculations show that the fraction of cohabiting couples is roughly 66 percent.[9] Thus, our sample consists of about two thirds cohabiting couples and one third non-cohabiting tenants. This raises the question whether, due to stronger social ties, motivational spillovers might be more pronounced among cohabiting couples than among non-cohabiting tenants. In section 3.3, we will address this question explicitly by formally examining heterogeneity in our sample.

[8]The BTSRC did not allow blood donations from homosexual individuals over the sample period we cover, thus ruling out same-sex couples.

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

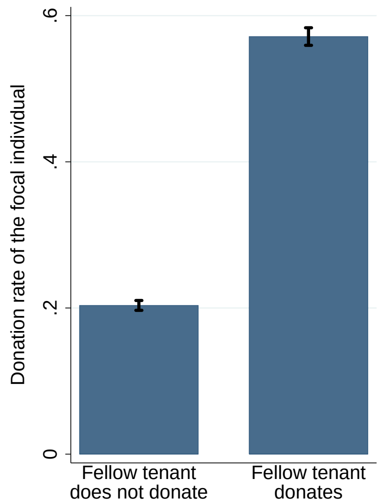

Figure 1: Donation rate of a focal individual conditional on whether the fellow tenant donates (with 95% CI)

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: $p < 0.001$			

Figure 1 shows the correlation between the individuals' donation decisions. Given that their fellow tenant donates blood, almost 60 percent of the individuals also donate themselves. If their fellow tenant does not donate, only 20 percent of the individuals donate. Table 2 illustrates this point from a different angle, by looking at the joint distribution of donations within dyads. It shows that 18.4% of all dyad-observations exhibit two donations upon both being invited, 27.6% show one donation, and 54% have no donations. Note that there are significantly more dyad-observations with either both individuals or no individual donating blood than expected under independence (χ^2-test for independent donations within dyads, p-value ≤ 0.001). Thus, donations within dyads are positively correlated.

However, as we pointed out in the introduction, the correlation in figure 1 and table 2 is not sufficient to show that social interaction between the individuals in a dyad exists. We are going to analyze this correlation in greater detail to determine the extent to which it is due to different types of social interaction.

2.3 Instrument for Identifying the Social Interaction Effects

The BTSRC uses phone calls to invited individuals to increase turnout for blood types that are in particularly short supply. It applies the following procedure. 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, and uses a software tool to put a random subset of invited individuals with matching blood types on a call list two days ahead of the blood drive.[10] As reported in Table 3, 8.9% of the individual observations in our sample received a phone call. In 1.40% of the dyad-observations both individuals received a phone call, in 14.99% of the dyad-observations only one individual was called, and in 83.61% of the dyad-observations no one received a phone call.

Since negative blood types are more versatile than positive ones, the BTSRC tends to call individuals with negative blood types more often. This could lead to the following issue: if individuals choose their fellow tenants conditionally on their blood types, and in particular, if individuals with negative blood types are more likely to live together, dyads in which both individuals exhibit negative blood types will be called more often and thus donate more often.[11] This would confound our estimate of endogenous social interaction effects. In order to rule out this potential issue, we compare the expected frequency of dyads with two negative blood types under independence with their observed frequency. Table 4 reveals that in our sample, 16.64% of individuals have negative blood types. Thus, the the expected frequency of dyads with two negative blood types under independence is 2.77%. This is not significantly different from the observed frequency of 2.98% (t-test, p-value=0.45). Consequently, we can rule out this potential issue.

Table 3: Descriptive statistics of the phone call

Variable	Mean	Std. Dev.	Corr. in dyad
Phone call	0.089	0.285	0.075
Share of dyad-observations without phone call	83.61%		
Share of dyad-observations with 1 phone call	14.99%		
Share of dyad-observations with 2 phone calls	1.40%		
# of observations	$10,120$		

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.” Note that since all individuals already received a personalized invitation letter plus a text message to remind them about the upcoming blood drive, the only additional information the phone call conveys is about the current scarcity of the recipient’s specific blood type. Nevertheless, the phone call is highly effective, raising donation rates by roughly 8 percentage points from a baseline of 30 percentage points (Bruhin et al. 2015). In sum, the phone call is triggered by random fluctuations in supply and demand, making it virtually as good as a random intervention, and it directly affects the recipient’s propensity to donate.

In order to be a valid instrument, we also need to assert that a phone call itself does not affect the fellow tenant’s propensity to donate directly, i.e. that it satisfies the exclusion restriction. In part, this

[10] The BTSRC confines the phone calls to blood types A-, A+, O-, or O+, as they are often in short supply.

[11] On grounds of a popular wisdom from East Asia, the correlation between personality and blood types have been extensively researched in psychology. However, there is no supporting evidence for such a correlation in the recent literature (see Wildman and Hollingsworth (2009), Cramer and Imaike (2002), Rogers and Glendon (2003), and Wu, Lindsted and Lee (2005)).

Table 4: Distribution of blood types

Variable	Mean	Std. Dev.	Corr. in dyad
Share of negative blood types			16.64%
Expected frequency of dyads with two individuals with negative blood types, under independence			2.77%
Observed frequency of dyads with two individuals with negative blood types			2.98%
T-test: observed frequency of all-negative dyads=2.77%			p=0.45
# of dyads			$3,723$

is guaranteed by the institutional setup. The BTSRC reaches the individuals during office hours on their mobile phones. Thus, the phone call does not directly affect the propensity to donate of the fellow tenant who is most likely not present at that time. Moreover, we present two tests in subsection 4.2 that address this issue more explicitly.

Next, we check that the phone call is indeed randomized conditional on blood types. This conditional randomization is crucial for the phone call being a valid instrument that is exogenous to all other individual characteristics that may drive donations or cause the individuals to live together in the same household. Table 5 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 (174 location fixed effects). But they are jointly insignificant in specification (3), with both location and 20 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 individuals entered the data set while the study was ongoing. These new individuals' donation history was necessarily zero at the time they received their first invitation. Because the month fixed effects pick up the resulting correlations, they are jointly insignificant in specification (3).

Table 5: 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
174 Location FEs?	no	yes	yes
20 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: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

2.4 Reduced-Form Evidence

In this subsection, we provide some first reduced-form evidence for the determinants of blood donations within dyads. This first reduced-form evidence highlights the key feature in our data that will later drive identification in the econometric model. However, in contrast to the econometric model, it neglects control variables and the standard errors do not take into account that each dyad is observed multiple times. Hence, it is for illustration only.

Figure 2 shows the reduced-form relationship between the phone call and donation rates. It provides a first glimpse at the qualitative order of magnitude of the potential social interaction effects. Panel a) shows the average change in the individuals' donation frequency if they receive a phone call: the donation frequency is 31 percent for individuals who do not receive a phone call, and increases by 13 percentage points if they are called. Panel b) shows the average change in the individuals' donation frequency if their fellow tenant receives a phone call: it increases by roughly 5 percentage points, with the confidence intervals sufficiently far apart to suggest a significant relationship.

As a simple illustrative tool to identify the impact of endogenous social interaction effects, we compare the magnitude of the effect of the fellow tenants' phone call on the individuals' behavior relative to that of the individuals' own phone call on their behavior, in the spirit of the Wald estimator. Since the fellow tenants' phone call does not have a direct impact on the individuals, we can use the relative magnitude of the two effects to identify social interaction effects among the individuals of the dyad: the estimates suggest a spillover of roughly $5\%/13\% = 0.38$, depicted in the rightmost panel of figure 2. This amounts to a strong impact among the individuals of the dyad on each others' decision to donate blood: given that an individual's fellow tenant donates, this raises her own probability of making a donation on average by 38 percentage points. Intriguingly, this is also close to the estimate from the "dirty" analysis that compares the individuals' donation rate as a function of whether their fellow tenants donated or not in Figure 1, suggesting only modest influences from common shocks that simultaneously drive the behavior of both individuals of the dyad.

The previous analysis shows evidence for endogenous social interaction effects, i.e. that a fellow tenant's decision to donate influences the other individual in a dyad. It is also interesting to ask whether there is evidence of exogenous social interaction, i.e. whether the fellow tenant's characteristics predict the other individual's donation. Figure 3 displays the individuals' current donation rate as a function of their own past donations (panel a) and their fellow tenants' past donations (panel b). Panel a) reveals that the individuals past donations strongly predict their current donations. Individuals who donated in the year before the study are almost 20 percentage points more likely to donate now than individuals who did not donate in the year before the study. However, panel b) shows that there appears to be no such relationship for the fellow tenants' donation histories: living with a fellow tenant who had donated regularly in the past does not increase an individual's propensity to donate. Overall, this first reduced-form evidence suggests that social interaction within dyads occurs through endogenous effects, and there is little evidence of exogenous effects.

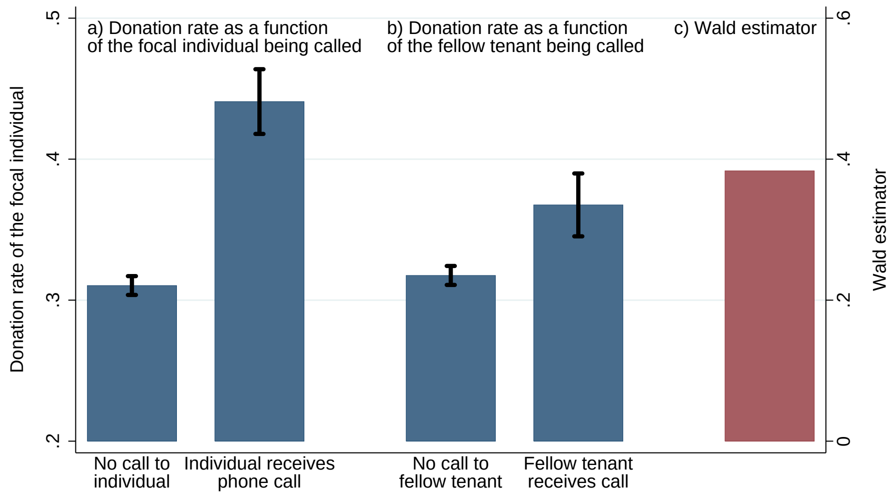

Figure 2: Donation frequency as function of the own phone call (panel a) and the fellow tenant's phone call (panel b). Including 95% confidence intervals and the Wald estimator.

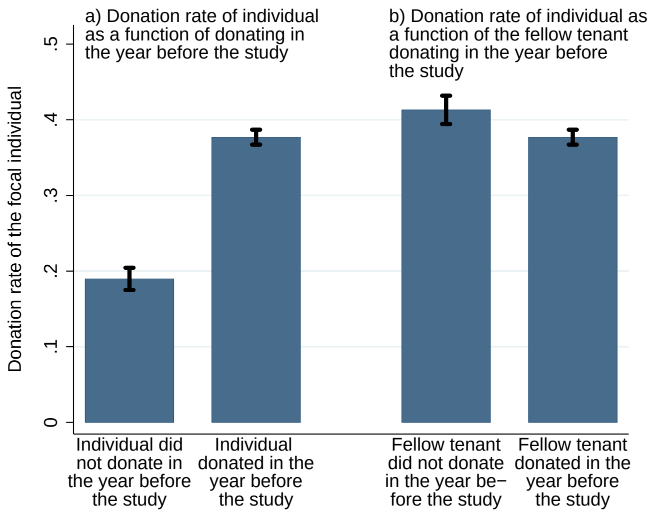

Figure 3: Donation frequency as function of the own past donations (panel a) and the fellow tenant's past donations (panel b). Including 95% confidence intervals.

3 Econometric Analysis

This section presents the econometric analysis for identifying endogenous and exogenous social interaction effects. 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

In the structural model, the immediate propensity of individual i in dyad d to donate 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 at time t in this subsection. β_0 is a constant, measuring the baseline propensity to donate. Y_{-id}^{*} indicates the propensity to donate of i's fellow tenant. Thus, the parameter δ captures the effect of endogenous social interaction, i.e. the extent to which the propensity to donate spills over within dyads. X_{id} represents individual i's 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 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 fellow tenants, 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 random errors 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: 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 errors in the structural form, ϵ_{1d} and ϵ_{2d}, 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_{1d} and ϵ_{2d} 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 or unobservable common shocks to the propensity to donate stemming from similar environments, thus making identification suspect if one imposed $\rho = 0$.

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

$$Y_{1d}^* = \beta_0 + \gamma P_{1d} + \delta Y_{2d}^* + \beta_2' X_{1d} + \beta_2' X_{2d} + \epsilon_{1d} \tag{3.6}$$

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

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 individual 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 fellow tenants: A fraction δ of the initial impulse to individual 1 also affects individual 2, which in turn feeds back into individual 1's propensity to donate, and so on. This amplifies the response to the phone call if $0 < \delta < 1$. For individual 2, the overall effect amounts to $\delta\frac{\gamma}{1-\delta^2}$, as only a fraction δ of individual 1's propensity to donate spills over to individual 2 (and because individual 1's phone call has no direct effect on individual 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 individual 2's phone call by the reduced-form coefficient of individual 1's phone call.[12] Having obtained δ, we can identify all remaining structural parameters: as is obvious from the

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

reduced form above, all other structural parameters are uniquely identified once δ is recovered (see section A.2 in the appendix on how to recover the structural parameters and calculate their standard errors).

A broad class of behavioral models give rise to the basic structure that we exploit in the econometric model to identify the key parameter of interest, δ. To illustrate, consider the following simultaneous-move game with imperfect information between two players: Each player has a benefit B from donating blood. Each player also draws a cost c_i from a uniform distribution on $[0, C]$ that only she observes, but not the other player. There is a consumption externality as the players each have an additional utility b if they donate together. That additional utility could have many possible sources. For instance, it could reflect image motivation from signaling the other player how motivated a player is. It could also reflect an additional benefit from spending time at the blood drive together, or simply a reduction in transportation costs.

In this model, increasing the motivation of one player leads to exactly the type of spillover effects that our structural model implies. Raising the benefit from donating to player 1 also raises the probability to donate of player 2, which in turn raises the probability to donate of player 1, and so on. Notice that both players have to know the other player's benefit from donating, but not the cost. One could for example imagine that the two players meet and tell each other about the phone calls, which informs them of the benefits. However, there needs to be some residual uncertainty about whether the other player donates, which we model through the cost of donating c_i that is realized later and is private information. The players then have to decide whether or not to donate without knowing the realization of the other player's cost. It turns out that in this particular example, a parameter $\delta \equiv b/C$ emerges in equilibrium that is related to the model's primitives, but acts as if the propensity to donate were spilled over as we postulate in the econometric model. That parameter in the behavioral model is identified precisely the same way as in the econometric model, by comparing the impact of the own phone call relative to the impact of the fellow tenants phone call on behavior (see appendix A.1 for a detailed derivation). While this game most closely reflects the structure of our model, one can also obtain the same result from another version of the simultaneous-move game in which the players know each others' cost realizations (see again appendix A.1 for details).

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.

3.3 Testing for Behavioral Heterogeneity

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[13]. As pointed out before, an estimated 66 percent of our individuals are cohabiting couples, and it is possible that social ties with regard to blood donations are stronger within cohabiting couples than among non-cohabiting 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.

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. 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 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 dyad d 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

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

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,

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

[13]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).

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^*, 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). [14]
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 $ICL\text{-}BIC$ 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 $ICL\text{-}BIC$ 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 $ICL\text{-}BIC$ 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 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 $ICL\text{-}BIC$ with respect to K.

[14] 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).

4 Results

This section presents the results of the econometric analysis. First, it discusses the estimated coefficients of the bivariate probit model in our baseline specification allowing us to distinguish between endogenous and exogenous social interaction. We then examine whether endogenous social interaction is driven by the transmission of motivation or information. Subsequently, we assess whether there is any evidence of behavioral heterogeneity with regard to social interaction. We also perform two robustness checks to evaluate the role of the functional-form assumptions implicit in the bivariate probit, as well as the role of the restriction in age difference that we impose on the sample.

4.1 Estimated coefficients of the Bivariate Probit Model

Table 6 shows the estimated coefficients for the structural equation in 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, which may affect both individuals in a dyad similarly. The 174 location fixed effects absorb differences between urban and rural areas as well as among the local organizers of the blood drives. The 20 month fixed effects pick up seasonal fluctuations or special events that 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 over 3. Its absolute magnitude is not directly interpretable, as it reflects the impact of the phone call on the individual's (latent) propensity to donate, Y^*, and not directly on her 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.6) in appendix A.3. These calculations reveal that the probability to donate increases by 9 percentage points for individuals who were on the call list, a sizable increase over the baseline donation rate of 32 percent. This estimate is virtually identical to the effect found in Bruhin et al. (2015), 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 pre-registered in the same blood drive. Thus, focusing on dyads does not induce selectivity in terms of how strongly individuals react to the phone call.

Next, we examine the extent of the endogenous social interaction effect within dyads. The corresponding parameter δ is significant in all three specifications. It is equal to 0.44 in the baseline specification of column (1). This implies that of a one-unit increase in the fellow tenant's propensity to donate roughly 44 percent spills over to the other individual in the dyad. Hence, an individual's propensity to donate blood strongly depends on her fellow tenant's propensity to donate. The estimates are slightly lower in columns (2) and (3) where we also include the location and month fixed effects. But even in the strictest specification of column (3), the parameter is equal to 0.39, implying that 39 percent of a fellow tenant's propensity to donate spill over to the other individual of the dyad.

Individual characteristics are strong determinants of blood donations. Men are significantly more likely to donate blood than women. This gender effect is robust and quantitatively important. The marginal effect of being male on the probability to donate is 4 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 donations in the year before entering the study predict current 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 donation rates (Wald-test for joint significance of all blood types, $p > 0.4$ in all specifications). In particular, individuals 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 specifications).

We now turn to the results regarding the effect of exogenous social interaction. A particularly interesting question in that context is whether it is just the fellow tenant's behavior per se, i.e. her immediate propensity to donate, an individual respond to, or whether it is also some other characteristics that are acquired with the behavior more generally. For instance, in studies documenting peer effects in schooling (Lalive and Cattaneo 2009; Cipollone and Rosolia 2007), it is probably not just the behavior per se (going to school), but also some characteristics acquired by it (getting a better education and a leg up in the labor market) that is driving the peer effects.

The fact that we have individual characteristics that strongly predict donations in general, in combination with a time-varying instrument, the phone call, allows us to address this issue. As mentioned above, an individual's age, gender and previous donations strongly predict her propensity to donate. Consequently, if the fellow tenant reacts to these characteristics and not just the actual behavior, we should in turn find that the fellow tenant's age, gender and previous donation history also affect the individual's propensity to donate. However, table 6 shows that this is not the case, as the fellow tenant's characteristics have, if anything, only weak effects on the individual's propensity to donate 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. Therefore, there is little evidence that individuals also react to the fellow tenant's exogenous characteristics, besides her immediate propensity to donate.

Finally, the estimates of ρ (the correlation of the errors in the structural model) lie 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, highlighting again the advantage of not relying on assumptions about ρ to identify our parameter of interest δ.

Table 6: 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)
Focal individual'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			
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			
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 errors	-0.275	-0.321	-0.198
in the structural form)	(0.380)	(0.377)	(0.413)
Wald-tests for joint significance (p-values)			
Focal individual:			
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
174 Location FEs?	no	yes	yes
20 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 Motivational vs. Informational Spillovers

Having established the existence of strong endogenous social interaction effects, we further investigate what is the main mechanism that drives them. Previous studies on peer effects in the context of prosocial behavior have concluded that the observed effects are due to spillovers of information rather than motivation (Lacetera, Macis and Slonim 2014; Bond et al. 2012; Drago, Mengel and Traxler 2013). In our context both mechanisms are possible. It is plausible that the baseline estimate presented in table 6 picks up the spillover from the motivational impulse of the phone call to the other tenant. However it is also possible that the the information about the scarcity of the blood type, communicated by the phone call, is transmitted within the dyad and that individuals respond to this information.

Our setup allows us to test for the the presence of an informational channel generating endogenous social interaction effects, and we provide two tests thereof. Our first test relies on compatibility of 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 potential donors very clearly. If it is information about the scarcity, rather than information about one's motivation that is transmitted between fellow tenants, then this effect should be stronger if they have compatible blood types.[15]

We are conducting these tests in the context of the reduced form of the bivariate probit model because the presence of an informational spillover does not allow us to use the structural form as before to identify the parameters.[16] We augment the reduced form in the bivariate probit model by adding the indicator $C_d = 1$ if a focal individual's blood type is compatible to the fellow tenant's blood type, and $C_d = 0$ otherwise. We add the interaction between C_d and the fellow tenant's phone call, and estimate

$$Y_{id}^* = \kappa_0 + \kappa_1 P_{id} + \kappa_2 P_{-id} + \kappa_3 C_d + \kappa_4 C_d \times P_{-id} + \kappa_5' X_{id} + \kappa_6' X_{-id} + u_{id}\,. \tag{4.1}$$

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

Table 7 displays the results. In the first two columns, it shows the reduced forms of the baseline specification with and without the indicator C_d. The third column, labeled "Validity Check 1a", 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, the interaction with the compatible blood type to the fellow tenant is not statistically significant. Therefore, there is no evidence that information about the scarcity of the blood type is transmitted, as individuals with incompatible blood types (which are not scarce at the moment), are no less affected by a phone call to their fellow tenant. Arguably not all individuals know about the compatibility of different blood types. Columns 4 and 5 show the same analysis but instead of using compatible blood types, we use identical blood types within dyads

[15] Compatibility in blood types works as follows. O is the universal donor and can give to everyone. A can give to A and AB. B can give to B and AB. AB can only give to AB. Regarding the Rh factor, negative blood types can give to positive blood types but not vice-versa for all blood types.

[16] Formally, informational spillovers within dyads cause a failure of the exclusion restriction we need to identify δ. For this reason, the checks can only be conducted in the reduced form.

(indicated by the binary variable) and its interaction with the fellow tenant's phone call indicator. The results are the same. Again, there is little evidence that information about the specific scarcity of the blood type is transmitted within dyads in a way that affects donation decisions.

A second way of checking for informational spillovers is based on the intuition that the phone calls may simply serve as a reminder of the blood drive. It is possible that the phone call to one fellow tenant also reminds the other of the blood drive, despite the invitation letter and the text message that everybody receives. 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 spillovers, the coefficient of the interaction should be significantly negative. Thus, we estimate the equation

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

The results of this validity check are displayed in the sixth column, labeled "Validity check 2" in Table 7. As can be seen, the point estimate of the coefficient of the fellow tenant's phone call remains positive and significant. The point estimate of the interaction of the two phone calls is positive – the opposite of what one would expect if information about the blood drive was transmitted – and insignificant. Hence, we find no evidence for informational spillovers and therefore interpret the endogenous social interaction effects as motivational spillovers.

Table 7: Bivariate probit model, reduced forms

Binary dependent variable: donation decision (0,1)						
Bivariate probit regression	Original Model	Augmented Original Model a	Validity Check 1a	Augmented Original Model b	Validity Check 1b	Validity Check 2
	(Eq. 3.8)	(Eq. 3.8 aug.)	(Eq. 4.1)			(Eq. 4.2)
P_{1d}	0.274***	0.275***	0.271***	0.275***	0.262***	0.268***
	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.052)
P_{2d}	0.106**	0.106**	0.100*	0.107**	0.090*	0.100*
	(0.051)	(0.051)	(0.055)	(0.051)	(0.053)	(0.053)
C_d		-0.022	-0.025			
		(0.048)	(0.050)			
$C_d \times P_{2d}$			0.032			
			(0.108)			
S_d				-0.046	-0.053*	
				(0.031)	(0.032)	
$S_d \times P_{2d}$					0.136	
					(0.122)	
$P_{1d} \times P_{2d}$						0.036
						(0.109)
$\bar{\rho}$	0.547***	0.547***	0.547***	0.547***	0.547***	0.547***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
# of observations	10,120	10,120	10,120	10,120	10,120	10,120
# of dyads	3,723	3,723	3,723	3,723	3,723	3,723
Log likelihood	-10,883.35	-10,883.19	-10,883.14	-10,881.69	-10881.12	-10,883.30
Wald-test $\xi_2 + \xi_3 = 0$						p=0.18

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

4.3 The Social Multiplier

Thus, taken together, our evidence suggests motivational spillovers as the source of endogenous social interaction. These spillovers generate a substantial social multiplier for policy interventions. To see how the phone call affects both individuals in a dyad, consider how the phone call to individual 1 changes her propensity to donate Y_1^*: its effect depends both on the phone call, and on the feedback induced by her fellow tenant, individual 2. Thus, $\Delta Y_1^* = \gamma + \delta \Delta Y_2^*$. Similarly, the fellow tenant 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 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: the spillovers amplify the effectiveness of the phone call for the individual called by a factor $1/(1-0.44^2) = 1.24$, and therefore by $0.44/(1-0.44^2) = 0.54$ for her fellow tenant, individual 2. Overall, this creates a social multiplier, equal to the sum of the two effects of $1/(1-0.44) = 1.79$. Even in the strictest specification, our estimate of δ is 0.39, implying a social multiplier of $1/(1-0.39) = 1.63$.

To illustrate the quantitative importance, we calculate the marginal effect of a phone call taking into account the feedback effects from the baseline specification (detailed in equations (A.7) and (A.8) in appendix A.3). We find that after individual 1 received a phone call, the increase in the probability to donate is 12 percentage points for individual 1. This contrasts with the estimated effect of the phone call shutting out the social feedback loop in our model (the impact operating through γ in our model), which raises donations by roughly 9 percentage points, and dovetails with the findings in Bruhin et al. (2015), where most individuals do not have a fellow tenant pre-registered for the same blood drive. In addition, the phone call to individual 1, raises the probability to donate by 5 percentage points for individual 2. Thus, motivational spillovers raise the overall effect of the phone call to 17 percentage points, whereas our model estimates suggest that for an individual without social ties, a phone call raises the probability to donate by only 9 percentage points.

4.4 Behavioral Heterogeneity

We next turn to examining behavioral heterogeneity. 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 in the literature, thus generating a further source of heterogeneity. We therefore estimate a finite mixture model that would pick up this sort of heterogeneity by identifying different types of dyads, even if type-membership is unrelated to observable characteristics.

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 8, 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.

Figure 4 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 5, 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 the baseline specification is a valid and parsimonious representation of the data.

Table 8: *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

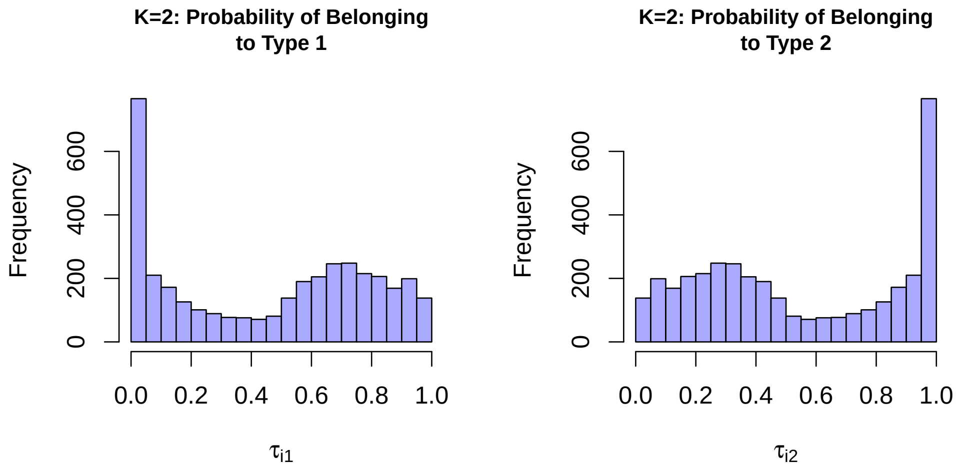

Figure 4: Ex-post probabilities of type-membership: model with $K = 2$ types

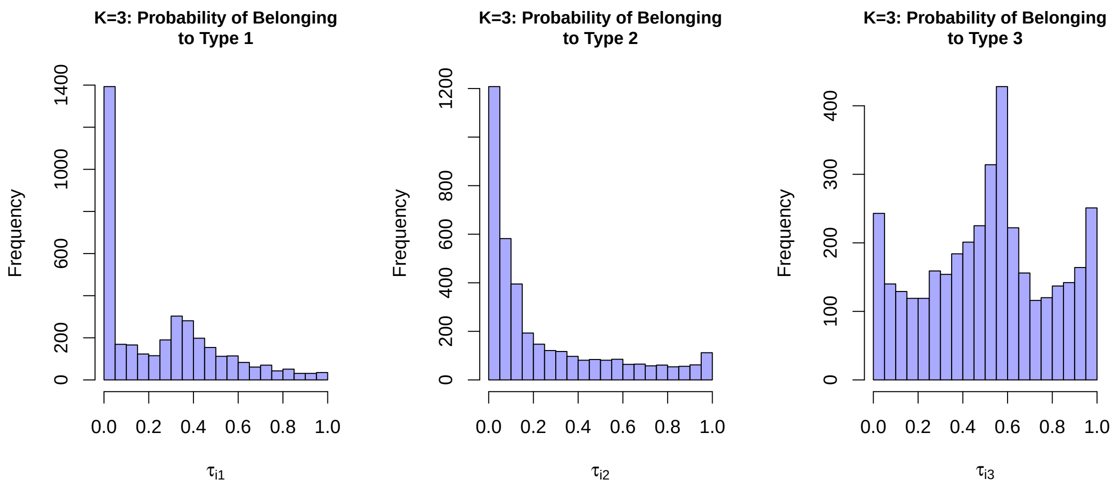

Figure 5: Ex-post probabilities of type-membership: model with $K = 3$ types

4.5 Robustness Checks

In this subsection, we evaluate the robustness of our results with respect to two ancillary assumptions of our empirical strategy. The first concerns the choice of the bivariate probit model and the functional form assumptions that it implies. The second concerns the restriction on the age difference within dyads.

TSLS Estimation of the Social Multiplier

In our baseline results, we use the bivariate probit model as the 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 therefore apply a linear probability model and use 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 the main 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[17]:

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

In the second stage, we regress the other individual's decision to donate 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 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.

Individuals who receive a phone call are about 8 percentage points more likely to donate blood than individuals 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

[17] Results of the first stage regression are reported in table 13 in the appendix.

Table 9: Linear probability model (second stage regressions)

Binary dependent variable: donation decision (0,1)

OLS regression	(1)	(2)	(3)
Phone call (ϕ_1)	0.084***	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)
Focal individual'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			
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			

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-statistics of instrument (1. Stage)	39.31	38.02	30.27
F-tests for joint significance (p-values)			
Focal individual:			
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
174 Location FEs?	no	yes	yes
20 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.

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. An individual's probability to donate blood increases by about 40 percentage points if her fellow tenant donates. In this model, again, the social multiplier is given by $1/(1-\phi_4)$. With a value of about 1.67, it lies in the same range as in 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 3 percentage points more likely to donate blood than women. This effect is statistically highly significant and robust. Donation rates increase with age. On average, an individual that is 10 years older donates 4 percentage points more often than the younger individual. 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 individuals' motivation (F-test for joint significance (1) p-value: 0.44, (2) p-value: 0.61, (3) p-value: 0.54). Individuals 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.

The Role of the Age-Difference Restriction

A perhaps somewhat 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 10 displays the results. We present the results in a more compact form, focusing only on the estimates of endogenous social interaction 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 age cutoffs.

Panel A of table 10 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.

Table 10: Bivariate probit model without age restriction

Panel A: Age difference restricted to less than 10 years

Bivariate probit regression	(1)	(2)	(3)
Phone call (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 errors	-0.303	-0.346	-0.219
in the structural form)	(0.440)	(0.438)	(0.485)
174 Location FEs?	no	yes	yes
20 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 call (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 errors	-0.083	-0.107	0.050
in the structural form)	(0.333)	(0.343)	(0.364)
174 Location FEs?	no	yes	yes
20 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

Models additionally include coefficients for X_{1d} and X_{2d} 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.

When we consider panel B of table 10, showing the estimates for the second sample with no age restriction, the number of dyads increases from $3,723$ to $5,053$, or by 35 percent. 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 10 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 δ 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 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 that issue.

5 Conclusion

In this paper we use a large panel data set with quasi-randomized phone calls to analyze the effects of social interaction on voluntary blood donations between fellow tenants. We find strong evidence for endogenous social interaction, which we interpret as 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 policy interventions by 63 to 79 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 conversations on the way and while waiting, or quite simply lower the (perceived) time costs of taking this activity in other ways. 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 others do so as well, as suggested in Sliwka (2007). Perhaps somewhat surprisingly, there is no evidence for the existence of different types of dyads that qualitatively differ in the extent or type of social interaction, making it – in our eyes – more likely that spillovers in motivation are due to joint consumption or lower costs of joint donation. However, all of the above interpretations are consistent with our results. Importantly, also the more "mundane" interpretations such as simply making donating more enjoyable (or less costly) in company, produce the same type of policy multiplier, as our model in the appendix illustrates.

Thus, irrespective of its source, the main finding of motivational spillovers has several policy implications. First, these motivational spillovers between fellow tenants are strong, and could therefore offset diminishing returns of policy interventions via social multipliers. Thus, applying policy interventions to groups of individuals in which motivational spillovers are likely present and strong – such as couples, flat mates, families, members of 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. Third, our results reinforce the notion that social forces may be highly effective levers to promote prosocial behavior. Lacetera, Macis and Slonim (2014) show that information about incentives spreads rapidly through donor networks. Our results show that motivation also spills over among donors, at least when social ties likely exist between them. Overall, this suggests that interventions putting social forces to work hold the promise of delivering effective policy interventions.

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. 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. Mechanisms that exploit social networks among, and social ties between individuals, are possible routes that could amplify traditional policy interventions aiming at increasing contributions to such public goods.

A Appendix

A.1 A Game-Theoretic Model Generating Motivational Spillovers

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 consumption externality in the activity: If both players engage in the activity, the benefits are increased by $b \geq 0$ for each of them. Each player also has a cost c_i of engaging in the prosocial activity. These costs are drawn from a uniform distribution, $[0, C]$. We consider two versions of the game. In the first version, each player's draw is known to him only, though the distribution is common knowledge. In this case, the game is a game of incomplete information, and has a unique mixed-strategy equilibrium that has straightforward interpretation in terms of our structural model. In particular, the strategy for identifying the social spillover parameter, that arises here from the strategic interaction, rather than actual utility spillovers, is exactly the same as in our econometric model. However, one may argue that players can communicate after they observe their private costs. We also address this 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 done as in our empirical model.

Version 1: incomplete information about c_i. In order to model the effect of the phone call, assume that only player 2 receives a phone call and that it raises his 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 phone call (or the extra utility γ to the other player). This lets us examine how, in equilibrium, the additional motivation γ spills over to player 1.

The game is a simultaneous-move game: each player has to decide whether or not to donate without knowing the other player's strategy. We are looking for the (unique) Nash equilibrium in this game. Player 1 will attend the blood drive if

$$B + p_2 b - c_1 \geq 0 \tag{A.1}$$

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

$$B + \gamma + p_1 b - c_2 \geq 0 \tag{A.2}$$

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 the uniform distribution yields a system of linear equations in p_1 and p_2:

$$p_2 = \frac{B + \gamma + p_1 b}{C}$$

and p_1 is given by

$$p_1 = \frac{B + p_2 b}{C}$$

Solving for p_1 and p_2, one obtains

$$p_1 = \frac{B}{C - b} + \gamma \frac{b}{C^2 - b^2}$$

and

$$p_2 = \frac{B}{C - b} + \gamma \frac{C}{C^2 - b^2}$$

It is instructive to define $\delta \equiv \frac{b}{C}$, which, in this setting, has the interpretation of being 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

$$p_1 = \frac{B}{C} \frac{1}{1 - \delta} + \frac{\gamma}{C} \frac{\delta}{1 - \delta^2}$$

and

$$p_2 = \frac{B}{C} \frac{1}{1 - \delta} + \frac{\gamma}{C} \frac{1}{1 - \delta^2}$$

Thus, the simple game we formulate provides the primitives for the econometric model that we estimate. It displays a social multiplier in the"reduced form"of donation probabilities exactly the way it is found in the econometric model. The ratio of coefficients on γ identify the spillover parameter δ in exactly the same way as in the econometric model: In general, any factor increasing utility of player 2 by one unit, spills over to player 1 by a proportion δ. It produces the same social multipliers that are relevant for policy as our econometric model.

Thus, the model outlined above provides a structural foundation of the model we estimate. Notice also, that in this setup, the parameter δ has a somewhat different interpretation: it is not directly a utility spillover, but rather a parameter produced by the optimal behavior given the other player's motivation that is related to the utility from joint donation b. Therefore, there are many possible psychological mechanisms that can lead to this type of spillover: in our model, b could be interpreted as image motivation, as suggested by Bénabou and Tirole (2011): being seen by a friend donating blood may increase one's utility because it increases one's image as a "good" person. It could also reflect the mere effect of enjoying to meet a friend at an occasion, or simply reflect a reduced cost of donating, e.g. because meeting a friend would lower transportation costs back from the blood drive.

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

$$\begin{aligned}\Pr(\text{Player 1 donates}) &= \Pr(c_1 < B) + \Pr(B < c_1 < B + b) \cdot \Pr(c_2 < B + b + \gamma) \\ &= \frac{B}{C} + \frac{b}{C}\frac{B + b + \gamma}{C} \\ &= \frac{B}{C} + \delta\frac{B + b}{C} + \delta\frac{\gamma}{C}\end{aligned} \tag{A.3}$$

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

$$\begin{aligned}\Pr(\text{Player 2 donates}) &= \Pr(c_2 < B + \gamma) + \Pr(B + \gamma < c_1 < B + b + \gamma) \cdot \Pr(c_1 < B + b) \\ &= \frac{B + \gamma}{C} + \frac{b}{C}\frac{B + b}{C} \\ &= \frac{B}{C} + \delta\frac{B + b}{C} + \frac{\gamma}{C}\end{aligned} \tag{A.4}$$

As can be seen from equations (A.3) and (A.4), the ratio of the impacts of γ on player 2 compared to player 1 identify again the spillover effect $\delta \equiv b/C$, as in the case with incomplete information. Thus, also in a simultaneous-move game with complete information, the same behavioral pattern that leads to a policy multiplier emerges. This widens the possible interpretations that can be given to b: for instance, it could also be a reduction in the transportation cost to go to the blood drive.

A.2 Recovering Parameters from the Reduced Form

Express equation 3.8 as

$$Y_{1d} = \alpha_0 + \alpha_1 P_{1d} + \alpha_2 P_{2d} + \alpha_3 X_{1d} + \alpha_4 X_{2d} + v_1 \tag{A.5}$$

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 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.3 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

$$\Delta P_{call} \equiv \Phi\left(\gamma_1 + \zeta'\overline{Z_d}\right) - \Phi\left(\zeta'\overline{Z_d}\right). \tag{A.6}$$

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

$$\Delta P_1 \equiv \Phi\left(\frac{\gamma_1}{1-\delta^2} + \zeta'\overline{Z_d}\right) - \Phi(\zeta'\overline{Z_d}), \tag{A.7}$$

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

$$\Delta P_2 \equiv \Phi\left(\frac{\gamma_1\delta}{1-\delta^2} + \zeta'\overline{Z_d}\right) - \Phi(\zeta'\overline{Z_d}), \tag{A.8}$$

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

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B Online Appendix

Table 11: Bivariate probit model with $\rho = 0$

Binary dependent variable: donation decision (0,1)			
Bivariate probit regression	(1)	(2)	(3)
Phone call (γ)	0.228***	0.236***	0.227***
	(0.066)	(0.067)	(0.063)
Endogenous social interaction (δ)	0.466***	0.456***	0.406**
	(0.167)	(0.170)	(0.185)
Constant (β_0)	-0.535***	-0.635***	-0.624***
	(0.170)	(0.218)	(0.239)
Focal individual's characteristics (β_1)			
Male	0.107***	0.097***	0.100***
	(0.024)	(0.024)	(0.025)
Age	0.013***	0.013***	0.013***
	(0.002)	(0.003)	(0.002)
# of donations in year before study			
1	0.513***	0.533***	0.541***
	(0.031)	(0.032)	(0.032)
2	0.859***	0.913***	0.922***
	(0.038)	(0.040)	(0.040)
3	1.034***	1.123***	1.137***
	(0.067)	(0.073)	(0.073)
4	1.004***	1.135***	1.119***
	(0.130)	(0.135)	(0.161)
Blood types			
O-	0.035	0.032	0.042
	(0.060)	(0.061)	(0.060)
A+	-0.031	-0.026	-0.026
	(0.023)	(0.024)	0.024)
A-	-0.012	0.008	0.008
	(0.049)	(0.048)	(0.047)
Fellow tenant's characteristics (β_2)			
Male	-0.009	-0.019	-0.012
	(0.031)	(0.030)	(0.032)
Age	-0.007**	-0.007**	-0.006*

	(0.003)	(0.003)	(0.003)
# donations in year before study			
1	-0.255***	-0.257***	-0.223**
	(0.090)	(0.095)	(0.105)
2	-0.402***	-0.387**	-0.336*
	(0.148)	(0.162)	(0.178)
3	-0.463**	-0.412*	-0.349
	(0.190)	(0.214)	(0.223)
4	-0.633***	-0.527*	-0.510*
	(0.241)	(0.274)	(0.298)
Blood Types			
O-	-0.042	-0.046	-0.036
	(0.057)	(0.058)	(0.060)
A+	0.010	0.013	0.011
	(0.024)	(0.024)	(0.025)
A-	-0.087**	-0.078*	-0.076*
	(0.040)	(0.043)	(0.043)
ρ (correlation between errors in the structural form)	0	0	0
Wald-tests for joint significance (p-values)			
Focal individual			
all blood types	0.44	0.65	0.57
negative blood types	0.68	0.87	0.77
non O-negative blood types	0.42	0.52	0.51
Fellow tenant:			
all characteristics	0.01	0.08	0.20
previous donations	0.05	0.04	0.14
all blood types	0.12	0.23	0.29
negative blood types	0.09	0.18	0.21
174 Location FEs?	no	yes	yes
20 Month FEs?	no	no	yes
# of observations	10,120	10,120	10,120
# of dyads	3,723	3,723	3,723
Log likelihood	-11,848.19	-11,466.89	-11,421.09

Household cluster robust standard errors in parentheses.

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

Age normalized to sample average.

B.1 Finite mixture regression results

Table 12: 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)	0.052	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)
Focal individual'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 errors	-0.988***	0.670
in the structural form)	(0.170)	(0.509)
π_k (share among the population)	0.456	0.544
	(0.060)	(0.060)
174 Location FEs?	yes	
20 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.

B.2 First stages of 2SLS

Table 13: 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 call (η_1)	0.104***	0.102***	0.093***
	(0.017)	(0.017)	(0.017)
Focal individual's phone call (η_2)	0.046***	0.045***	0.035**
	(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)
Focal individual'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
174 Location FEs?	no	yes	yes
20 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.